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NONDESTRUCTIVE PAVEMENT EVALUATION USING ILLI-PAVE BASED ARTIFICIAL NEURAL NETWORK MODELS

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Nondestructive Pavement Evaluation Using ILLI-PAVE Based Artificial Neural Network Models

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EXECUTIVE SUMMARY

The overall objective in this research project is to develop advanced pavement structural analysis models for more accurate solutions with fast computation schemes. Soft computing and modeling approaches, specifically the Artificial Neural Network (ANN) and Genetic Algorithm (GA) techniques, have been implemented to develop forward and backcalculation type pavement analysis models based on the validated nonlinear ILLI-PAVE finite element solutions of the most commonly found/constructed flexible pavements in the State of Illinois. The developed pavement evaluation toolbox can be used for rapidly and more accurately backcalculating field or in-service pavement layer properties and thicknesses; predicting critical stress, strain, and deformation responses of these in-service pavements in real time from the measured Falling Weight Deflectometer (FWD) deflection data; and incorporating these predicted critical pavement responses, such as tensile strain for asphalt fatigue, directly into the Illinois Department of Transportation's (IDOT's) mechanistic pavement analysis and design with emphasis on extended life asphalt pavement design concepts. The outcome of the project's successful research efforts now provides IDOT with a field validated nondestructive pavement evaluation professional ANN (ANN-Pro) software package to assess pavement condition through FWD backcalculation and eventually help assess pavement rehabilitation strategies. In addition, a second software package also developed in the project provides the framework SOFTSYS, Soft Computing Based Pavement and Geomaterial System Analyzer, which estimates full-depth asphalt pavement thickness when there is no thickness data available for the pavement section where FWD testing is performed.

CHAPTER 1: INTRODUCTION

1.1 OVERVIEW AND PROBLEM STATEMENT

Evaluating structural condition of existing, in-service pavements constitutes annually a major part of the maintenance and rehabilitation activities undertaken by State Highway Agencies including Illinois Department of Transportation (IDOT). Accurate estimation of pavement geometry and layer material properties through the use of proper nondestructive testing and sensor technologies is very important for evaluating pavement's structural condition and determining options for maintenance and rehabilitation. For this purpose, pavement deflection basins gathered from the nondestructive Falling Weight Deflectometer (FWD) test data are commonly used to evaluate pavement structural conditions. Often these interpretations of FWD test data also require the layer thicknesses of the tested pavements for backcalculation of the pavement layer properties. With the recent AASHTO move towards adopting mechanistic based pavement analysis and design concepts and procedures nationwide, interpretations of FWD data from routine nondestructive testing currently demands the use of advanced multi-layered and finite element (FE) solutions for proper analyses of pavement structural conditions. According to IDOT's mechanistic based pavement analysis and design, algorithms based on the ILLI-PAVE FE solutions are used for this evaluation (Thompson 1989). Recently, use of artificial neural network models trained with ILLI-PAVE FE solutions proved to make considerable improvements over the statistical algorithms currently in use.

In the past 15 years, there has been an increased interest in a new class of computational intelligence system, known as artificial neural networks (ANNs), for use in pavement systems applications. ANNs have been found to be powerful and versatile computational tools for organizing and correlating information in ways that have proven useful for solving certain types of problems too complex, too poorly understood, or too resource-intensive to tackle using more-traditional computational methods. ANNs have been successfully used for tasks involving pattern recognition, function approximation, optimization, forecasting, data retrieval, and automatic control, to name just a few.

As ANNs are a useful complement, while being superior in performance, to more-traditional numerical and statistical methods, their use has been primarily in the following areas: materials characterization/modeling, pavement distress classification, pavement structural modeling, pavement performance prediction, and finally, pavement rehabilitation in the forms of nondestructive evaluation and remaining life estimation. There have been several successful studies of using ANNs to predict the pavement layer moduli using the Falling Weight Deflectometer (FWD) deflection data (Gucunski and Krstic 1996; Gucunski et al. 1998; Ioannides et al. 1996; Khazanovich and Roesler 1997; Kim and Kim 1998; Lee et al. 1998; Meier et al. 1997; Meier and Rix 1993; Meier and Rix 1994; Meier and Rix 1995; Williams and Gucunski 1995). The NCHRP1-37A research project team working on the development of the new Mechanistic-Empirical Pavement Design Guide (MEPDG) have also recognized ANNs as nontraditional, yet very powerful computing techniques and took advantage of ANN models in preparing the MEPDG concrete pavement analysis package (http://www.trb.org/mepdg/). The power of ANNs in pattern recognition and their superiority for correlating nonlinear relationships between the inputs and outputs of a problem make them an excellent tool for the structural evaluation of pavements using both static and dynamic deflection basins. Among the various State DOT's and government agencies that have already used ANNs in nondestructive evaluation of pavements are:

(1) Texas DOT with a primary use in the development of a methodology based on ANNs to compute the remaining life of flexible pavements and compare results with field data from the Texas Mobile Load Simulator (Abdallah et al. 1999);

(2) Kansas DOT used ANN-based distress models to predict longitudinal joint spalling for concrete pavements in Kansas (Basheer and Najjar 1996); and

(3) Waterways Experiment Station employed ANNs as surrogates for WESLEA in a computer program for backcalculating pavement layer moduli and cutting the processing time drastically (Meier et al. 1997).

In recent successful applications at the University of Illinois, the use of ANNs was introduced for backcalculating the pavement layer moduli and predicting the critical pavement responses directly from the Falling Weight Deflectometer (FWD) deflection basins (Ceylan et al. 2004). ILLI-PAVE 2005 finite element program (Elliott and Thompson 1985; Thompson 1987; Thompson 1992; Thompson 1994; Gomez-Ramirez and Thompson 2001), extensively tested and validated for over three decades, has been used as the primary analysis tool for the solution of full-depth and conventional flexible pavement responses under the standard 9,000-lb FWD loading. ANN models then trained with the results of the ILLI-PAVE FE solutions have been found to be viable alternatives to backcalculate the pavement layer moduli and predict the critical pavement responses based on the FWD deflection data. The trained ANN models are capable of backcalculating the pavement layer moduli and predicting the maximum stresses and strains with very low average absolute errors of those obtained directly from ILLI-PAVE analyses. These error magnitudes are commonly much smaller than the ILLI-PAVE algorithms currently in use by IDOT. The direct prediction of critical pavement responses from the FWD deflection basins also offers an added advantage when used together with IDOT's mechanistic based pavement design.

When properly trained ANN models are used as surrogate advanced ILLI-PAVE structural models to backcalculate pavement layer properties, the speed of these ANN models can be used as an advantage in traditional backcalculation schemes. With the combination of a powerful and robust searching algorithm, such as Genetic Algorithms (GAs), additionally pavement layer thicknesses can be estimated from just the FWD deflection basins. Thickness variability is a real issue in the field, and coring is not always an option to determine layer thickness. It is also one of the key inputs to the pavement management systems. With this idea, the SOFTSYS approach has been under development to the extent that its full potential will be demonstrated based on the current promise for truly nondestructive pavement analysis.

1.2 RESEARCH OBJECTIVES

The overall objective in this research project is to develop Artificial Neural Network (ANN) models based on the ILLI-PAVE finite element solutions as a pavement evaluation toolbox for:

1) rapidly and more accurately backcalculating field or in-service pavement layer properties;
2) predicting critical stress, strain, and deformation responses of these in-service pavements in real time from the measured FWD deflection data;
3) incorporating these predicted critical pavement responses, such as tensile strain for asphalt fatigue, directly into IDOT's mechanistic pavement analysis and design with emphasis on extended life asphalt pavement design concepts.

In addition to these objectives, the motivation of this research study has also been to develop the framework SOFTSYS, Soft Computing Based Pavement & Geomaterial System Analyzer, with the purpose of:

1) determining pavement thickness for Full-Depth Asphalt Pavements (FDP) as well as the pavement layer properties reliably using FWD deflection basin data without any coring requirements in the field;
2) extending the possibility of using SOFTSYS for Full-Depth Asphalt Pavements on Lime Stabilized Soils (FDP-LSS) in order to cover wider ranges of pavements in Illinois; and
3) validating further the results of SOFTSYS with the field data obtained using Ground Penetrating Radar (GPR) as well as the core thickness data obtained from the road sections where GPR is performed.

By successful completion of this study, the intent has been to provide IDOT engineers with a field validated nondestructive pavement evaluation professional ANN (ANN-Pro) model toolbox to assess pavement condition and eventually help assess pavement rehabilitation strategies. In addition, SOFTSYS program has been developed to provide solutions when there is no thickness data available for the pavement section, where FWD testing is performed.

1.3 RESEARCH METHODOLOGY

The research was performed following the major tasks for reaching the study goals:

Task 1: Work with the FWD team of the IDOT Bureau of Materials and Physical Research and Districts to identify the types and properties of different flexible pavement layers existing in Illinois.

Task 2: Conduct ILLI-PAVE finite element (FE) runs on the commonly found/ constructed flexible pavement sections considering stress-dependent pavement layer behavior. A database of FE runs will be developed covering the different pavement layer thicknesses, layer moduli, and deformation characteristics of the pavement layers.

Task 3: Develop forward and backcalculation type ANN models based on the ILLI-PAVE FE solutions for the evaluation of flexible pavement systems. Different ANN architectures will be searched and trained to determine the optimum network architecture (or model) that best captures the behavior of pavement sections in Illinois. Several different network architectures will be trained using different number of input parameters. Some of the network architectures will be designed for directly predicting the critical pavement responses (maximum stresses, strains and deflections) from the FWD deflection basins. These networks will be crucial for implementing the mechanistic-based pavement design concepts.

Task 4: Use both existing FWD data, available and gathered from previous Illinois Cooperative Highway Research Program studies, and new field FWD data, collected in recent years by IDOT engineers running FWD tests, to validate the ANN models.

Task 5: Prepare an ANN based forward and backcalculation structural analysis toolbox as user-friendly software and demonstrate the use of this toolbox with real world examples and applications.

Task 6: Develop models for SOFTSYS full-depth asphalt pavement layer properties and thicknesses and calibrate these models linking to the actual field FWD data available from IDOT. The results will need to be verified with the actual field data. GPR is selected as the most reliable way of determining thickness of pavement sections. In addition, construction thickness information is required to determine the thickness of the pavements. The variability in the thickness as well as other pavement properties is a critical issue. Therefore, along with the FWD testing, GPR testing will also be performed on selected full-depth asphalt pavement sections.

1.4 REPORT ORGANIZATION

Chapter 2 of this report introduces FWD testing as the most popular pavement nondestructive testing and evaluation approach and gives a complete literature review of the backcalculation methods including the background information provided on the advanced methods used in this study, i.e., ANNs and Genetic Algorithms (GAs). The development of ANN based structural models are described in Chapter 3 for full-depth asphalt and conventional type pavements found/constructed in Illinois on both natural and lime stabilized subgrade soils. The developed ANN models are also validated with field FWD data in Chapter 3. Chapter 4 introduces the SOFTSYS approach based on the combined use of ANNs and GAs for pavement layer modulus and thickness determinations applied mainly to full-depth asphalt pavements. Chapter 4 also includes field validation of the SOFTSYS methodology. Finally, a summary and the major findings of the research study are given in Chapter 5.

CHAPTER 2: LITERATURE SURVEY

In the area of transportation geotechnics, the practice of determining the pavement layer properties using surface deflections is commonly referred to as backcalculation. The backcalculation of layer properties including pavement layer moduli and even layer thicknesses from surface deflection measurements plays a major role in the structural evaluation of pavements, design of overlays and management of in-service pavements. There are mainly two approaches to determine the existing condition of a pavement; either by destructive or non-destructive means. In the last three decades, the improvements in technology have caused the non-destructive testing (NDT) methods to become more popular since there is neither disturbance to the integrity of the material nor the sampling of it. Moreover, they are quite easy to use, repeatable, and they can be performed much more rapidly than destructive tests. These advantages result in much less overall cost in the long run when compared to those of the destructive testing methods. Against all the advantages, the reliability of NDT methods certainly depends on the accurate interpretations of the test results and the precise determination of the pavement layer material properties, such as pavement layer stiffness or modulus and layer thickness. Falling Weight Deflectometer (FWD) testing is the most popular NDT method for evaluating pavements. It provides pavement surface deflections recorded by several offset sensors in response to a constant load dropped from a specific distance at a certain frequency. These deflections are essentially used for structural evaluation of pavements.

2.1 FALLING WEIGHT DEFLECTOMETER TESTING

Falling Weight Deflectometers (FWDs) have been known as NDT devices which can exert an impulsive load on the pavement and record the resulting deflections on the pavement surfaces at several distances from the load. As the name implies, an FWD imparts its test load by means of a specified weight (usually between 110 and 660 lbs.) falling a given distance (up to 16 in.) and striking a buffered plate resting on the pavement surface (see Figure 2-1). It can produce a peak dynamic force typically between 1,500 and 24,000 lbs in 25-30 milliseconds (see Figure 2-2). The load is transmitted from the rubber buffers to pavement through a 5.91-in. radius steel plate underlain by a rubber pad, which helps applying the load uniformly on the pavement surface. The FWD impulse load duration of 25 to 30 milliseconds approximates the same load duration of a vehicle traveling at 40 to 50 mph (Ulliditz and Stubstad 1985).

Deflections with FWD equipment are typically measured at the center of the load and up to six other locations. A typical test configuration is shown in Figure 2-3. One advantage of FWD is that it is better than any other testing equipment in replicating the load histories and deflections produced by moving vehicles. This deflection profile or basin is primarily affected by the properties of individual pavement layers as well as the magnitude and frequency of the loading (Shahin 2005). In comparing elastic properties calculated from an earlier Dynaflect test with results from the FWD, it was found that dynamic effects were less important in the FWD results due to the higher frequencies (Roesset and Shao 1985). Hoffman and Thompson (1981) compared the FWD with the Road Rater Model 400B and the Benkelman Beam NDT equipment. They concluded that the FWD produced a deflection which best represented conditions under a moving wheel load. Since FWD is the closest device for duplicating the deflections of a moving truck (Ulliditz and Stubstad (1985), it has been widely accepted in the world. Among many FWD's described in the literature, the three most commonly used and commercially available ones are the following:

1) Dynatest Model 8000 (Dynatest Consulting, Inc.);
2) KUAB FWD Models 50 and 150 (KUAB America);

3) JILS FWD (Foundation Mechanics, Inc.).

IDOT has been using the most commonly utilized FWD device, Dynatest Model 8000 (see Figure 2-1). It is a trailer mounted device which may be towed by passenger vehicles. In 2007, IDOT purchased a JILS 20T truck-mounted FWD.

Figure 2-1. Dynatest FWD device used by IDOT.

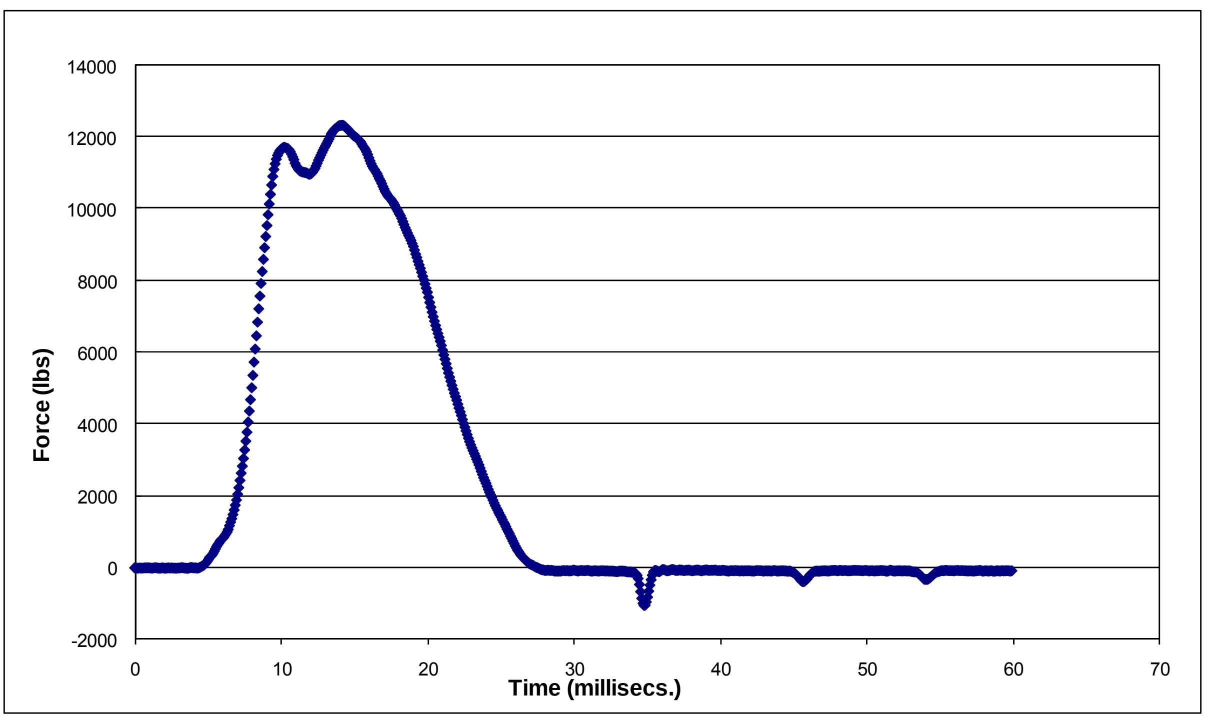


Figure 2-2. Haversine loading applied by FWD.

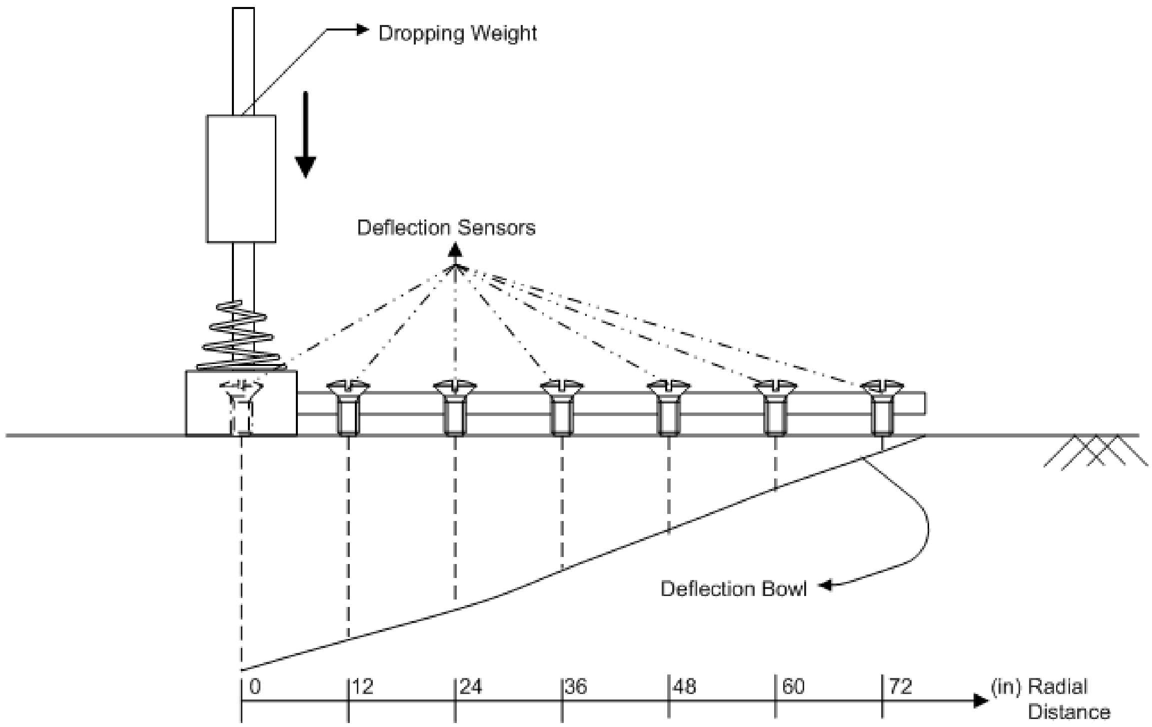


Figure 2-3. Locations of FWD sensors and schematic drawing.

FWD test deflection basins can be successfully interpreted to identify the existing condition of a pavement under traffic loading. For example, at a specified temperature, small deflections may indicate the response of a strong pavement structure, while larger ones might dictate the existence of weaker sections. Diagnosing the current conditions of pavements, however, requires inversion of mechanical properties through evaluation of FWD data.

2.2. BACKCALCULATION METHODS

Backcalculation is an inverse type of engineering problem, which is generally hard to solve analytically due to its ill-posed nature. The sensitivity of solutions, i.e., backcalculated layer properties, to the deflections as the variables of the inverse problem is generally quite high. In addition, the solutions typically require searching of a multidimensional nonlinear space formed by the variables, where traditional numerical approaches do not operate well (Liu and Han 2003). The computational procedure to solve this problem effectively usually includes both a pavement response model and an optimization algorithm. Indeed, the key elements for the effective solution are to understand the nature of the problem and to select the appropriate methodology that relaxes the complexity of the inversion process.

The concept of backcalculation for pavements became popular in the last three decades along with wide use of mechanistic-empirical methods in the design of pavements and developments in pavement management systems. Backcalculation approaches for obtaining pavement moduli using NDT data can be grouped into three methods (Anderson 1988):

- Simplified methods;
- Gradient relaxation methods;
- Direct interpolation methods.

Among all of them, the most popular ones are gradient relaxation methods. In this type, generally a mathematical model of the pavement is constructed and subjected to the appropriate NDT load to obtain surface deflections as a function of pavement layer properties. This model can then be run with various layer properties until a satisfactory solution set is found for which the measured deflection basin is produced (see Figure 2-4).

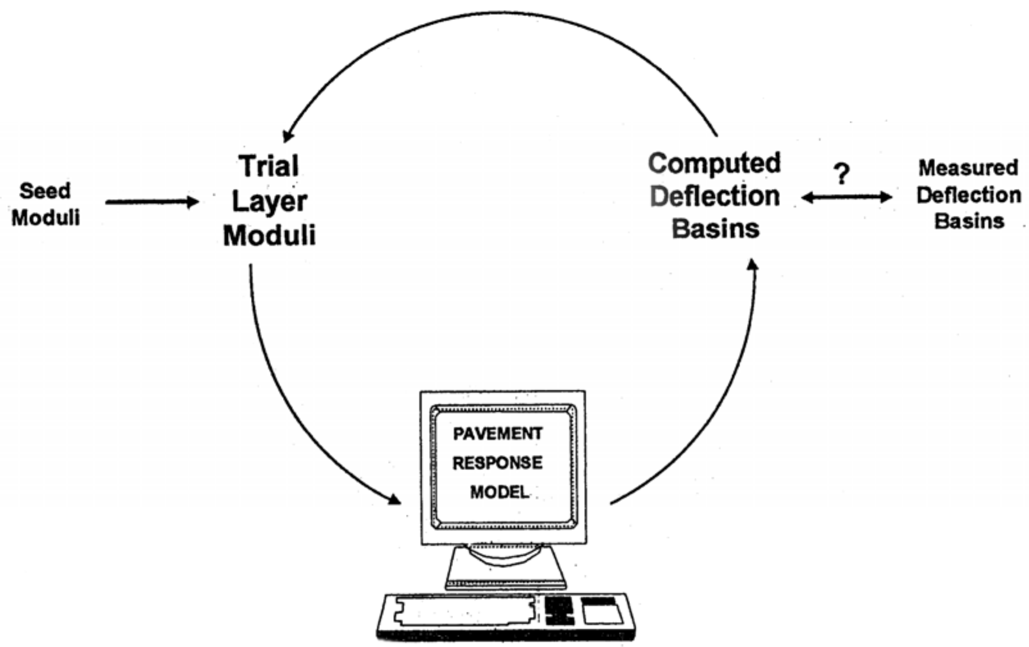


Figure 2-4. Traditional iterative backcalculation procedure (Meier 1995).

Alkasawneh summarized (2007) the main steps of the backcalculation as follows:

- Define the input parameters of the pavement system including: thickness of each layer, Poisson's ratio, etc.
- Assume moduli seed values for the pavement system. Seed moduli values can be assumed based on experience or based on typical moduli values. Moduli values can be different based on the forward method implemented in the backcalculation program.
- Calculate the pavement deflections, using the forward program, at the FWD geophone locations (along the surface).
- Compare the calculated deflections with the measured deflections. If the difference between the calculated and measured deflections is acceptable, then

the assumed layer moduli are the actual moduli. Otherwise, the assumed layer moduli are not the actual moduli and the assumed moduli should be refined.

- Repeat steps if necessary.

In addition to these, many computational methods were proposed. Linear regression methods, artificial neural networks (ANNs), genetic algorithms (GAs), and fuzzy systems were mainly utilized as backcalculation techniques. A recent study by Goktepe et al. (2006) provides an extensive summary of these methods. Particularly, many researchers found soft computing methods to be useful due to their advantages such as non-universality and noise tolerance (Ghaboussi 2001; Ghaboussi and Wu 1998), which can properly deal with the difficulties naturally existing in the backcalculation problem. As a sub-class of soft computing methods, the development of ANNs and GAs for pavement backcalculation studies will be reviewed.

2.3 ARTIFICIAL NEURAL NETWORKS (ANN'S)

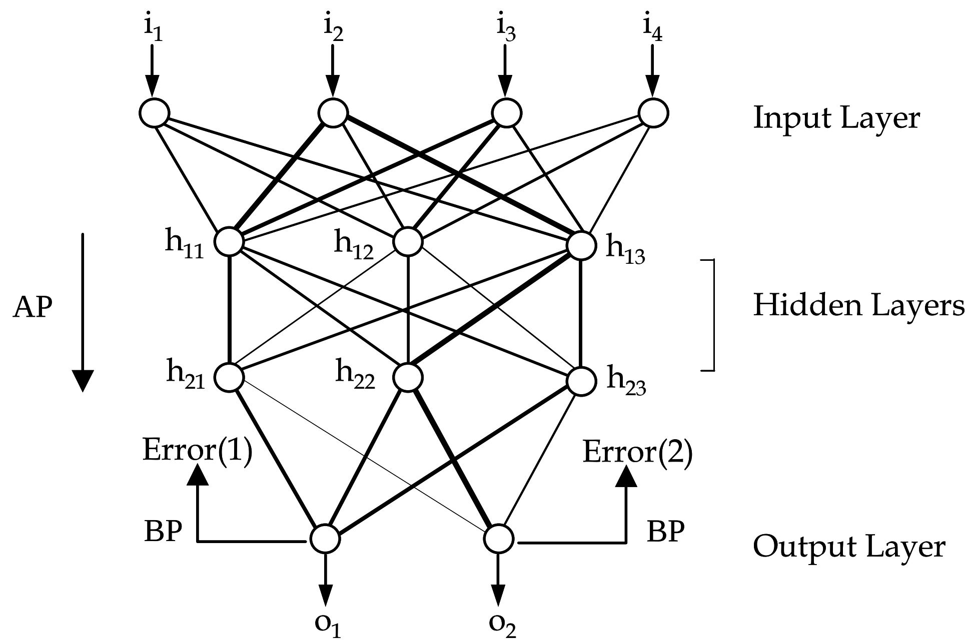
ANNs are computational models for information processing. ANNs are mainly classified as a subclass of soft computing tools that duplicate some of their fundamental properties from biological systems (Haykin 1999; Hertz et al. 1991; Reed and Marks 1999). They can be trained to perform certain tasks. They are mainly used as one of the most powerful data-mining methods. They can tolerate the error in the dataset to a certain extent (called imprecision tolerance) and they are mostly valid within the ranges of the training datasets (called non-universality). They are quite robust and practical techniques for computationally complex problems (Ghaboussi 2001). In many civil engineering applications, they are used as nontraditional computing tools that can capture nonlinear relationships between inputs and outputs of natural phenomena or any numerical methods such that well established non-linear regression tools fail due to the complex nature of the problem (Ghaboussi and Wu 1998).

The main type of Artificial Neural Networks (ANN) is referred to as a multilayer, feed-forward neural network which was composed of single processing elements called perceptrons (Rosenblatt 1958). The following are essential to feed forward neural networks: (1) A feed-forward propagation rule, (2) a network topology (i.e., the number of nodes, layers, and their connectivity), and (3) a learning rule.

The error back-propagation algorithm (also known as the generalized delta rule) is the most commonly used learning rule. The feed-forward neural networks which use the error back-propagation learning rule are generally referred to as back-propagation neural networks. A typical back-propagation neural network used in this study is sketched in Figure 2-5. The multilayered back-propagation ANN has usually one input layer, one output layer, and the constructed processing elements (artificial neurons) named as hidden layers. The hidden layers are sandwiched between the input and output layers. The network operation consists of a highly nonlinear functional mapping of the neurons in hidden layers between the input and output variables.

2.3.1 Backpropagation Learning Algorithm

In perceptrons, each artificial neuron or processing element receives several input signals X_j originating from previous nodes and then processes each signal considering its connection weight W_{ij} (see Figure 2-6). The relationship between the input signals and the level of internal activity of the processing element is given by:



AP : Direction of Activation Propagation;

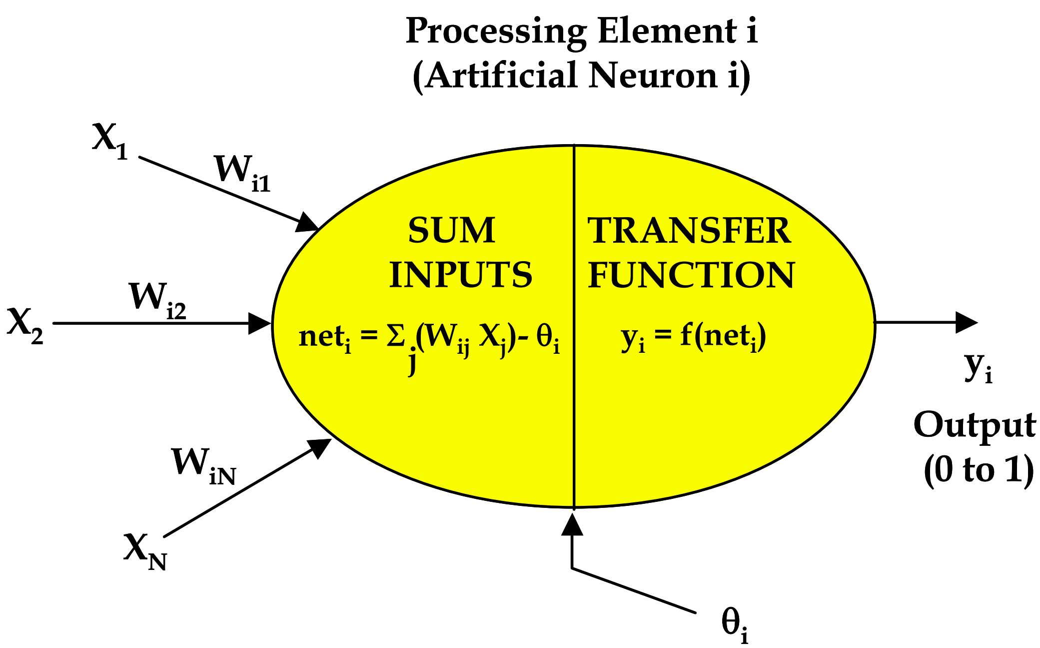
BP : Direction of Error Back-Propagation;

i_1 to i_4 : Input variables;

h_{11} to h_{23} : Artificial neurons (processing elements);

o_1 to o_2 : Output variables.

Figure 2-5. A typical backpropagation neural network.



$X_{1,\,2,\,\ldots,\,N}$: Set of Inputs;

W_{ij} : Connection Weights (Strength of a Single Biological Synaptic Connection);

θ_i : Bias Term (Corresponds to an Activation Threshold);

net_i : Net Input Signal (Level of Internal Activity);

Transfer Function : $f(x) = 1/(1+e^{-x})$, Sigmoidal Function.

Figure 2-6. Summation and transfer functions of a typical artificial neuron.

$$\mathrm{net_i} = \sum_{j=1}^{N}(\mathrm{W_{ij}}\ \mathrm{X_j}) - \theta_i \quad (2\text{-}1)$$

where net_i = Net input signal (level of internal activity);
W_{ij} = Connection weight between artificial neurons i and j;
X_j = Value of signal coming from previous node j;
θ_i = Bias term of node i (corresponds to an activation threshold);
N=Number of input signals from previous nodes.

When the weighted sum of the input signals exceeds the activation threshold θ_i, the artificial neuron outputs a signal y_i dictated by a transfer function f(x). The output signal is then expressed as a function of the net input signal by:

$$\mathrm{y_i} = \mathrm{f}(\mathrm{net_i}) \quad (2\text{-}2)$$

where

$$f(x) = \frac{1}{(1+e^{-x})} \quad (2\text{-}3)$$

is a sigmoidal function which gives a value between 0 and 1 for the output y_i.

The neural network modifies the connection weights between the layers and the node biases in ensuing iterations to allow a type of learning for the network. The weights and node biases are shifted until the error between the desired output and the actual output is minimized. The learning process is described as follows: "Learning (or training) is the process whose objective is to adjust the link weights and node biases so that when presented with a set of inputs, ANN produces the desired outputs."

After each feed-forward sweep of the ANN is completed in the direction of activation, the squared error terms E^k between the outputs y_i and the target values t_i (actual values in the output layer) are computed from the following:

$$\mathrm{E}^{\mathrm{k}} = \frac{1}{2}\sum_{\mathrm{i}}[\mathrm{t_i^k} - \mathrm{y_i^k}]^2 \quad (2\text{-}4)$$

where i denotes the individual neurons, and superscript k represents the individual data values from the training data set. Note that the output y_i in the above equation is actually a function of the sigmoidal function given in Equation 2-3.

The change in the connection weights (ΔW_{ij}) between the nodes to be adjusted during the learning process is related to the minimization of the average squared error E. To minimize the squared error E^k, the derivative of the error with respect to the connection weight W_{ij} between nodes i and j is required as follows:

$$\Delta\mathrm{W_{ij}} = -\eta\frac{\partial\mathrm{E}}{\partial\mathrm{W_{ij}}} = -\eta\ \sum_{\mathrm{k}}\left(\frac{\partial\mathrm{E}^{\mathrm{k}}}{\partial\mathrm{W_{ij}}}\right) \quad (2\text{-}5)$$

where η is a learning coefficient > 0. Using the chain rule of differentiation, the derivative term $\partial E^k/\partial W_{ij}$ can now be written as:

$$-\frac{\partial E^k}{\partial W_{ij}} = -\frac{\partial E^k}{\partial y_i}\frac{\partial y_i}{\partial net_i}\frac{\partial net_i}{\partial W_{ij}} = -\delta_i^k \frac{\partial net_i}{\partial W_{ij}} = -\delta_i^k X_j \qquad (2\text{-}6)$$

in which $\delta_i^k = (\partial y_i / \partial net_i)*(\partial net_i / \partial W_{ij})$ is defined as "delta" term of the generalized delta rule and is given by:

$$\delta_i^k = \begin{cases} (t_i^k - y_i^k)\ f'(net_i^k) & \text{for output layers} \\ \sum_m \delta_m^k W_{im}\ f'(net_i^k) & \text{for hidden layers} \end{cases} \qquad (2\text{-}7)$$

where the letter "m" represents the nodes in the network below the current i'th layer towards the output layer (see Figure 2-5). Since the back-propagation algorithm starts from the output layer, the calculations progress implicitly in the direction towards the input layer. The derivative of the sigmoidal function f′(x) to be used in the above equation can be given in terms of the function:

$$f'(x) = f(x)\ \{1 - f(x)\} \qquad (2\text{-}8)$$

now substitute Equation 2-8 in Equation 2-7 for easy computation of deltas.

During each iteration (it), the connection weights from node j to i are updated as follows:

$$W_{ij}(it+1) = W_{ij}(it) + \eta \sum_k \delta_i^k\ X_j^k + \alpha\ [W_{ij}(it) - W_{ij}(it-1)] \qquad (2\text{-}9)$$

where α is called the momentum (or acceleration) term added to stabilize the training process. The summation is done over all individual data in the training set. The inputs to the nodes in the back-propagation direction are taken from the outputs of the nodes in the preceding layer, i.e., $X_j^k = y_j^k = o_j^k$ (for the first hidden layer). Similarly, the bias term θ_i is also updated at each iteration by an equation of the form:

$$\theta_i(it+1) = \theta_i(it) + \eta \sum_k \delta_i^k + \alpha\ [\theta_i(it) - \theta_i(it-1)] \qquad (2\text{-}10)$$

As the iterations progress, the network repeatedly cycles through the training set. The parameters α and η in Equations 2-9 and 2-10 help provide an accurate approximation of the unknown mean squared error (MSE) minimum. Iterations must be continued until an apparent decrease in the maximum MSE to an acceptable level is observed. By using the momentum term α in the search, settling into a local minimum or oscillating endlessly about the global minimum can be prevented.

2.3.2 FWD Backcalculation using ANNs

When FWD backcalculation is considered, an ANN model can be trained to map deflection basins back onto their corresponding pavement layer moduli. One way to train such a network would be to use experimentally determined deflection basins along with independently measured pavement layer thicknesses and moduli. However, it is often difficult to obtain representative, undisturbed samples with which to make a laboratory determination of the pavement moduli. Furthermore, because laboratory testing is expensive, there is an insufficient quantity of experimental data covering a broad-enough range of pavement layer moduli and pavement layer thicknesses to successfully train a neural network (Meier 1995).

Instead, synthetic deflection basins calculated using pavement analysis programs such as ILLI-PAVE can be used to create synthetic deflection basins. This allows precise control of the pavement layer properties used to train the network. The basic neural network training procedure developed for this study can be viewed as a closed loop (see Figure 2-7). A mathematical model is used to calculate a synthetic deflection basin for a presumed set of pavement layer properties. The artificial neural network is then taught to perform the inverse operation of mapping the synthetic deflection basin back onto the presumed set of properties. At first, the neural network produces a random mapping; however, by repeating the training process many times for many different pavement profiles, the neural network will eventually learn the appropriate inversion function (Meier 1995).

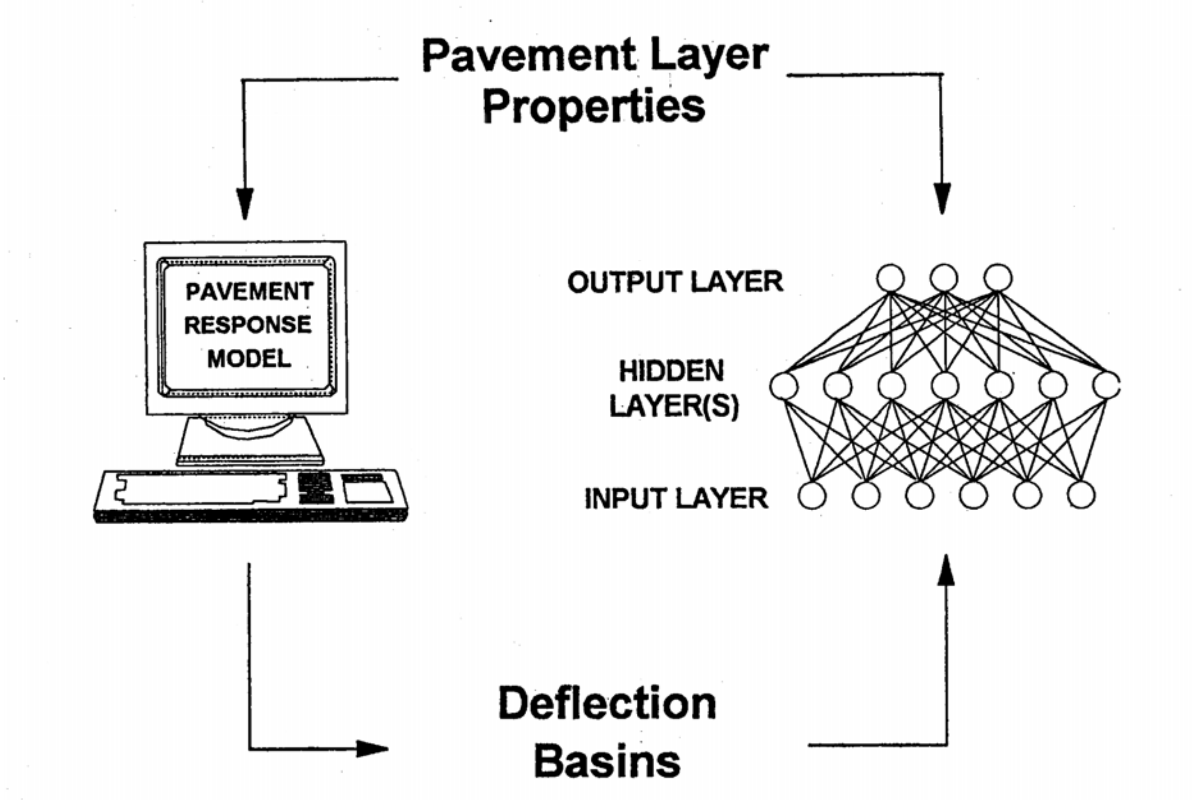
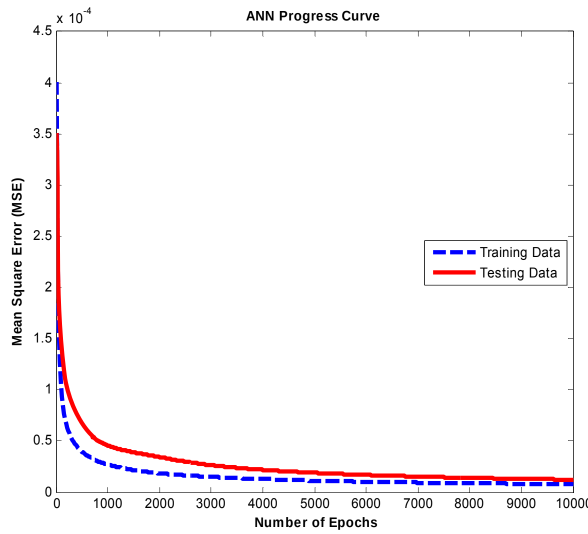
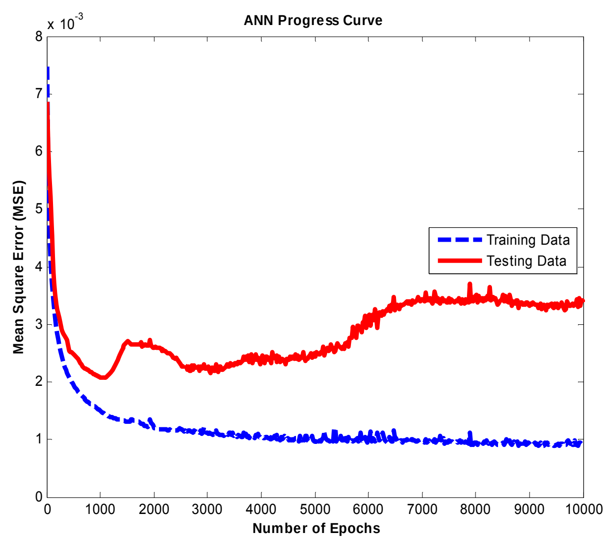


Figure 2-7. Traditional iterative backcalculation procedure (Meier 1995).

Trained ANN models need to be tested based on an independent dataset within the ranges that they were trained. A sufficiently wide dataset obtained from the pavement analysis can be chosen independently considering the given ranges of material and geometry properties and used as the testing dataset for the verification of proper ANN learning. The remaining data are then used for the training and learning procedure. Whether the trained ANN models are capable of producing the same database (with the given inputs to obtain outputs or vice versa) can be checked quickly in this manner. Figure 2-8(a) and (b) show proper and improper learning curves for training and testing datasets. Improper learning causes ANNs to memorize the given training dataset and to lose the capability of generalization (Reed and Marks 1999). Although training takes a long computation time, testing is often much faster (on the order of micro seconds) with the already set weighted connections. This advantage also facilitates the use of trained ANNs as quick pavement analysis tools for a field engineer to use them without the need for any complex inputs.



(a) proper learning



(b) improper learning

Figure 2-8. Typical ANN learning curves.

2.4 GENETIC ALGORITHMS (GA'S)

Genetic algorithms are the randomly directed search techniques that mimic natural evolution in its form and search operators. The defining components of a genetic algorithm (GA) are as follows:

- The genotype/phenotype representation of the problem domain;
- Fitness evaluation;
- Selection scheme;
- Crossover method;
- Mutation rate.

Variations in each of the above items have been examined by researchers, and several generations of improvements within each area have been realized. The theory describing the behavior of GAs, however, remains grounded in the schema theorem and the principle of minimal building blocks as defined by Holland (1975) and Goldberg (1989). Both principles recommend the selection of a representation of fixed length that encodes the parameters of the problem in binary form. This is readily confirmed by the vast number of applications that use this standard GA representation.

GAs were introduced by Holland (1975) as a technique that supports adaptation in natural and artificial systems. Most of the research that followed, however, realized that GAs provided a method highly suited for performing optimization. De Jong (1975) investigated the performance of GAs as function optimizers by applying a simplified GA, which consisted of roulette wheel selection, simple crossover, and simple mutation, to a test bed of five functions. This GA formulation has become known as the simple GA (SGA). In the same research effort, De Jong also studied several variations of the SGA that included providing elitism and crowding during the selection process. Goldberg (1989) provides a thorough research review on the different GA proposed formulations and discusses the results obtained from applying SGAs to numerous applications. Currently, the majority of the GA optimization applications use the structure of the SGA in conjunction with fitness proportional selection or tournament selection.

SGAs and traditional optimization methods can be applied to the same optimization problems. SGAs have four features that make them fundamentally different from traditional optimization methods (Goldberg 1989; Raich 1999):

(1) GAs decodes variables, they do not utilize them directly;
(2) GAs considers a population of solutions, they do not emphasize a single solution;
(3) GAs do not extra information such as derivatives of the variables;
(4) GAs use probabilistic transition rules, not deterministic ones.

These features provide flexibility in applying SGAs to diverse and sometimes previously unapproachable set of optimization problems. The representation of the objective function and constraints and the ability to handle discrete variable types without requiring logical constraints are among some advantages(Raich 1999). More importantly, working with a population of individuals instead of a single individual reduces the chance of converging to a local optimum.

GAs borrow the following genetic terms to explain the form and processing of the GA representation and operators (Raich 1999):

- Gene => encoded parameter value;
- Allele => all possible values that can be encoded for a specific parameter;
- Genotype => the total encoded parameter information in the GA string;
- Phenotype => the decoded solution from the GA string;
- Crossover => exchanging string segments between two selected GA strings;

- Mutation => changing a single bit or value randomly on a single GA string; and
- Selection => performing a "survival of the fittest" reproduction of GA strings.

In GAs, a single solution represented by a string is called an individual, and the set of solutions is termed a population of individuals. The fitness evaluation for each solution is provided for different design cases that are called environments. A single iteration of the GA is a generation; the entire GA search time is the evolutionary time (Raich 1999).

Many researchers have investigated the application of GAs in optimization and design (Michalewicz 1996). The benefits of GAs over other methods used in search, including mathematical programming and heuristic search methods are (Rasheed and Hirsh 1997):

- The provision of a global search method, which is more effective for searching multi-modal and deceptive problem domains than the local search methods provided by traditional and heuristic search methods.
- The ability to easily incorporate discrete, continuous, and mixed variables into the constraint formulation.
- The ability to handle arbitrary objective functions that are nonlinear, discontinuous, ill-defined, and deceptive without requiring gradient information.
- The ability to perform fitness evaluations and genetic manipulations independently for each individual, which makes GAs suitable for parallel computation.

2.4.1 Simple Genetic Algorithms (SGA's)

SGAs are identified by the use of three standard genetic operators: selection scheme (generally roulette wheel selection), simple crossover, and simple mutation as defined by Goldberg (1989). These three genetic operators are applied to a population of fixed length strings consisting solely of binary bits (0 or 1) that represent a fixed set of parameter values. Real or integer parameter values are encoded in the string in a predetermined order using "n" bit binary representation for each parameter. The resulting string of binary bits is called the genotype. Simple crossover and mutation are performed on the genotype. The binary bit strings are decoded into the real or integer parameter values to obtain the solution, which is called the phenotype. The expressed phenotype provides the solution evaluated by the fitness function.

The steps required to apply the SGA are shown in Figure 2-9 (Raich 1999). The designer selects the size of the population and randomly initializes all of the individuals in the population. The solution represented by each individual is decoded from the genotype and evaluated using the defined fitness function. The genetic operations of selection, crossover, and mutation are then performed to determine the new population. The iterative process of evaluation and genetic manipulation is continued until convergence is reached. The SGA evolutionary search process is summarized in six steps:

1) Generate random initial population of n individuals;
2) Determine the fitness of each individual;
3) Select n individuals based on fitness using fitness proportional selection;
4) Perform crossover and mutation on selected individuals;
5) Form new population of n individuals; and
6) Repeat steps 2 through 5 until the stopping criterion is satisfied.

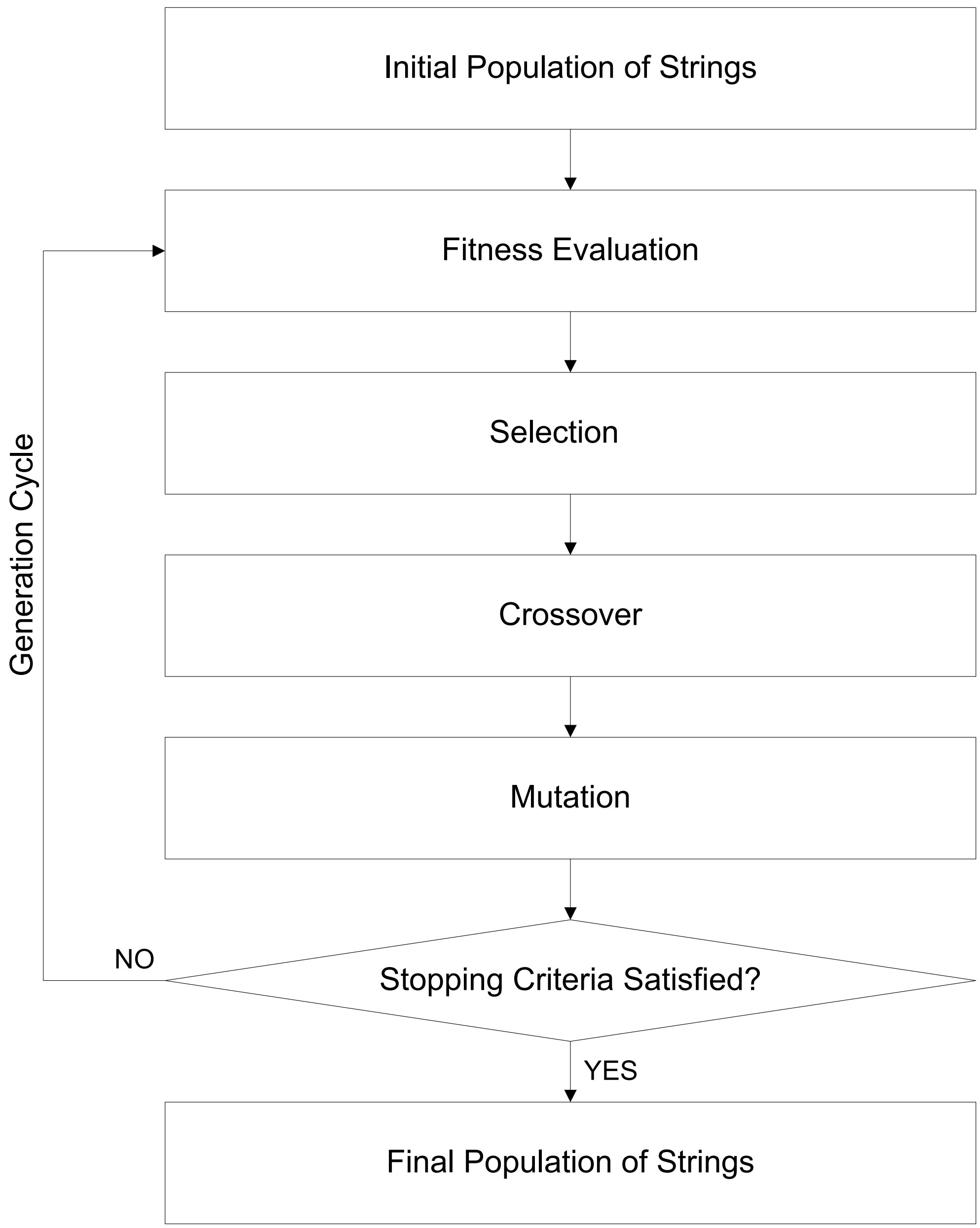


Figure 2-9. Simple genetic algorithm (SGA) (Raich 1999).

2.4.1.1 Simple Genetic Algorithm Genotype/Phenotype Representation

In SGAs, each parameter value is represented as “n” bit binary number. The encoded binary values are concatenated together to form a binary string. The order of the encoding is predetermined by n one to one mapping of the parameter values to the encoded binary values. The string length is fixed in SGA and is determined by adding the lengths of the individual n bit binary numbers. The number of bits, n, used to encode each parameter sets explicitly the range of the parameter values, such as a 2-bit binary number that is used to represent the integer numbers (0,1,2,3). If other ranges of integer or decimal precision numbers are required, a mapping is used to adjust the ranges for continuous parameters or to assign values for discrete parameters. An example for multivariable phenotype representation is provided in Tables 2.1 and 2.2.

Table 2.1. Real Value Representation of Phenotypes

Population	Variable 1	Variable 2	Variable 3
1	17	89	21
2	25	54	10
3			
4			
5			
…	… … …	… … …	… … …
…			
…			
maxPop			

Table 2.2. Bit String Representation of Phenotypes for Use in Genetic Algorithms

Population	Variable 1					Variable 2							Variable 3				
#	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	1	0	0	0	1	1	0	1	1	0	0	1	1	0	1	0	1
2	1	1	0	0	1	0	1	1	0	1	1	0	0	1	0	1	0
3																	
4																	
5																	
…	…					…							…				
…	…					…							…				
…	…					…							…				
max Pop																	

2.4.1.2 Roulette Wheel Selection in Simple Genetic Algorithm

Roulette wheel selection, which is also called fitness proportional selection, was one of the first selection methods investigated and is still popular in GAs. A fitness value is assigned to each individual based on the evaluation of the defined fitness function, and individuals of the population are selected in proportion to their fitness. Each individual j in the population will have a probability of selection $r(x_j)$ based on its fitness value $f(x_j)$ divided by the sum of the fitness values of the population (Equation 2-11):

$$\rho(x_j) = \frac{f(x_j)}{\sum_{i=1}^{m} f(x_i)} \tag{2-11}$$

where m is the number of individuals in the population.

An individual with a high fitness will have an increased chance of being selected for recombination; those individuals with low fitness may not be selected at all.

Example: Suppose it is desired to maximize the function given in Equation 2-12

$$z = (x-7)^2 + (y-3)^2 \tag{2-12}$$

with both x and y given on an integer interval [0,7]. For this function, the roulette wheel algorithm is explained in Table 2.3:

Table 2.3. Randomly Created Initial Population for the Example Problem
(Population Size = 4)

(a) Initial Population -j	(b) Phenotype (x,y)	(c) Fitness (f_i)	(d) Genotype (x,y)	(e) Normalized Fitness (%) (f_i /SUM)	(f) $S_i = \sum_{i=1}^{j} f_i$	(g) Random Number Generator b/w 0-100	(h) New Parent ID
1	(4,1)	13	100001	12.7	12.7	67	4
2	(1,4)	37	001100	36.3	49.0	1	1
3	(6,2)	2	110010	2.0	51.0	69	4
4	(0,4)	50	000100	49.0	100.0	8	1
SUM		102			100		

- The members of the population are numbered.
- Let's assume that the initial population is created randomly for (x,y) in [0,7] interval.
- The fitness values (in this case, it is function we want to maximize) are calculated.
- Phenotypes are encoded into Genotypes using 3 bits to represent x and y separately. The bit values for "x" and "y" are then combined together to form a bit string.
- The fitness values are normalized with respect to SUM of all fitness.
- Cumulative sum is used to rank the fitness along a straight line between 1 and 100. It gives the sum of all fitness values from individual one to individual i.
- Random Number Generator is used to create random numbers between 0 and 100.
- The first individual whose cumulative sum S_i is equal or greater than this integer will be chosen as a parent.

2.4.1.3 Genetic Manipulation in Simple Genetic Algorithm

In SGAs, two individuals are randomly paired from the set of selected individuals to undergo single point crossover. For each pair of strings, a bit location is selected randomly, the string is cut virtually at this location (called locus), and the portions of the strings beyond the cut are exchanged as shown in Figure 2-10. Crossover supports the recombination of good building blocks by placing the building blocks in new contexts on different individuals (Holland 1975).

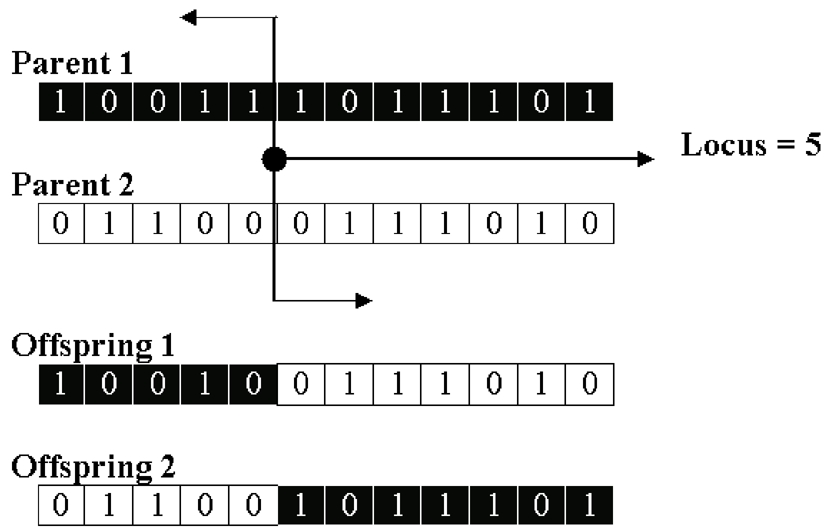


Figure 2-10. Crossover operation.

Bit mutations are used by SGAs to prevent the loss of diversity in the population by introducing new genetic information or reintroducing previously lost information (Goldberg 1989). For the SGA binary representation, a mutation is applied probabilistically to each bit in an individual by flipping the bit value from zero to one, or vice versa (see Figure 2-11). The mutation rate typically is set at a low level of about 1 mutation per 1000 bits. After mutation has been performed, the new population consists of the children created by the process of crossover and mutation from the parents selected from the population.

The SGA continues the evolution process until a maximum number of generations is reached or a stated convergence criteria has been satisfied for the fitness or population convergence.

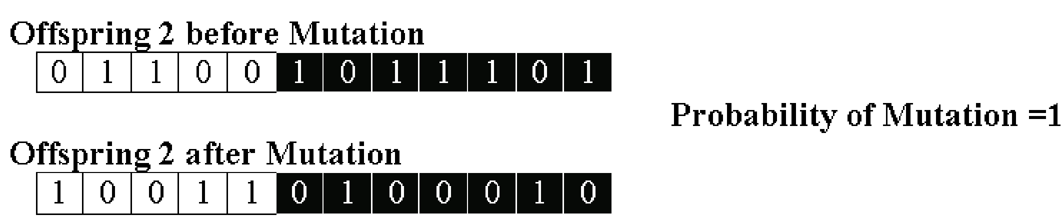


Figure 2-11. Mutation operation with probability of mutation = 1.

2.4.2 Genetic Algorithms in Backcalculation

GAs were effectively utilized for the solution of pavement layer backcalculation problem in the past. A binary coded simple genetic algorithm (SGA) (Goldberg 1989) with single point crossover, mutation and ranking selection mechanism was first introduced as a novel method for backcalculation of pavement layer moduli (Fwa et al. 1997). In this study, a deflection based objective function was utilized, which seeks for matching deflections calculated from one of the two different deflection computation approaches (BISAR or Odemark equivalent layer method) with that from FWD testing. It was also proven that the

SGA algorithm approach performed better when compared to conventional backcalculation software that implements different search routines. A similar approach was later developed for backcalculation of pavement layers with the deflection values obtained from elastic layer system analyses (Kameyama et al. 1998). The method of heuristic crossover for floating point implementation was used along with dynamic mutation operator. Moreover, the implemented ranking selection was modified through exterminating the resembling chromosomes to prevent the danger of premature convergence. Reddy et al. (2002) developed a GA based backcalculation program that implements the same philosophy using an elastic layered pavement software to compute surface deflections. Reddy et al. (2004) also later determined a set of optimum parameters for backcalculating pavement layer properties using elastic programs. The optimal set of GA parameters (population size, crossover and mutation probabilities) was determined using a heuristic approach implemented through running a GA based backcalculation program called BACKGA.

The papers referenced above (Al-Khoury et al. 2001; Ceylan et al. 2005; Fwa et al. 1997; Goktepe et al. 2006; Kameyama et al. 1998; Loizos and Plati 2007; Meier et al. 1997; Pichler et al. 2003; Rakesh et al. 2006; Reddy et al. 2002; Reddy et al. 2004; Saltan and Terzi 2004; Willett et al. 2006) describe the computational approaches to determine the pavement layer properties. Most of the methodologies presented there can only estimate pavement layer properties with the already known design thicknesses. The ones that can determine the thickness, however, require large computational time. Moreover, they all require advanced material properties to be known in advance, which is very expensive and difficult. As a result, they are not practical to implement in the field or even as a theory based solution to the problem.

The previous studies proved that GAs were successful in finding the solution for the backcalculation problem. However, all the proposed methodologies use the solutions of elastic layered programs or the programs mainly employed at the design stage of pavements for matching deflections obtained from FWD tests. On the other hand, loading conditions for pavements induce high nonlinearity in material behavior. Therefore, proper pavement modeling requires consideration of nonlinear pavement layer properties, which makes the solution of the backcalculation problem even more difficult.

In this project, the applicability and performance of a new SGA approach adopted is investigated to backcalculate the layer moduli and thicknesses of full-depth asphalt pavements in the field using the pavement responses obtained from the nonlinear finite element program ILLI-PAVE solutions.

CHAPTER 3: ARTIFICIAL NEURAL NETWORK BASED STRUCTURAL MODELS

In this chapter, the development of Artificial Neural Network (ANN) structural models for both forward and backcalculation type pavement structural analyses is introduced. Forward analysis models are the ones used to analyze pavement sections without the need for using a pavement analysis program while the backcalculation models are used to backcalculate pavement layer properties directly from Falling Weight Deflectometer (FWD) test results. Considering the ANN model development stages, nonlinear finite element modeling of flexible pavements is discussed first along with its relevant aspects on pavement layer characterization. Lime stabilization of pavement weak subgrades is also described to address the need for performing separate analyses for pavements built on lime stabilized sections. The process of ANN model training is explained next by giving details of the additional computer programs also developed for collecting and processing the synthetically generated data from thousands of finite element analyses. Finally, the details of the developed forward and backcalculation analysis ANN structural models are given with their performance validations accomplished through the use of field FWD data.

3.1 ILLI-PAVE FINITE ELEMENT MODELING

ILLI-PAVE 2005 finite element (FE) program, the most recent version of this extensively tested and validated ILLI-PAVE pavement analysis program for over three decades, was used as an advanced structural model for solving deflection profiles and responses of the typical Illinois full-depth pavements (FDP) and conventional flexible pavements (CFP), full-depth pavements on lime stabilized soils (FDP-LSS) and conventional flexible pavements on lime stabilized soils (CFP-LSS). ILLI-PAVE uses an axisymmetric revolution of the cross-section to model the layered flexible pavement structure. Unlike the linear elastic theory commonly used in pavement analysis, nonlinear unbound aggregate base and subgrade soil characterization models are used in the ILLI-PAVE program to account for typical hardening behavior of base course granular materials and softening nature of fine-grained subgrade soils under increasing stress states. Among the several modifications implemented in the new ILLI-PAVE 2005 finite element code are:

1) increased number of elements (degrees of freedom);
2) new/updated material models for the granular materials and subgrade soils;
3) enhanced iterative solution methods;
4) Fortran 90 coding and compilation, and
5) a new user-friendly Borland Delphi pre-/post-processing interface to assist in the analysis (Gomez-Ramirez et al. 2002) (see Figure 3-1).

3.1.1 Falling Weight Deflectometer Simulation

Pavement FE modeling was performed in this study using an axisymmetric (FE) mesh for all pavement sections considered. Using ILLI-PAVE FE program, FWD tests on flexible pavements were modeled with the standard 9-kip equivalent single axle loading applied as uniform pressure of 80 psi over a circular area of 6 in. radius. The FE mesh was selected according to the uniform spacing option of the FWD sensors as follows: 0 in., 8 in., 12 in., 18 in., 24 in., 36 in., 48 in., 60 in. and 72 in. away from the center of the FWD plate. The surface deflections corresponding to the locations of these FWD sensors were abbreviated as D_0, D_8, D_{12}, D_{18}, D_{24}, D_{36}, D_{48}, D_{60} and D_{72}, respectively.

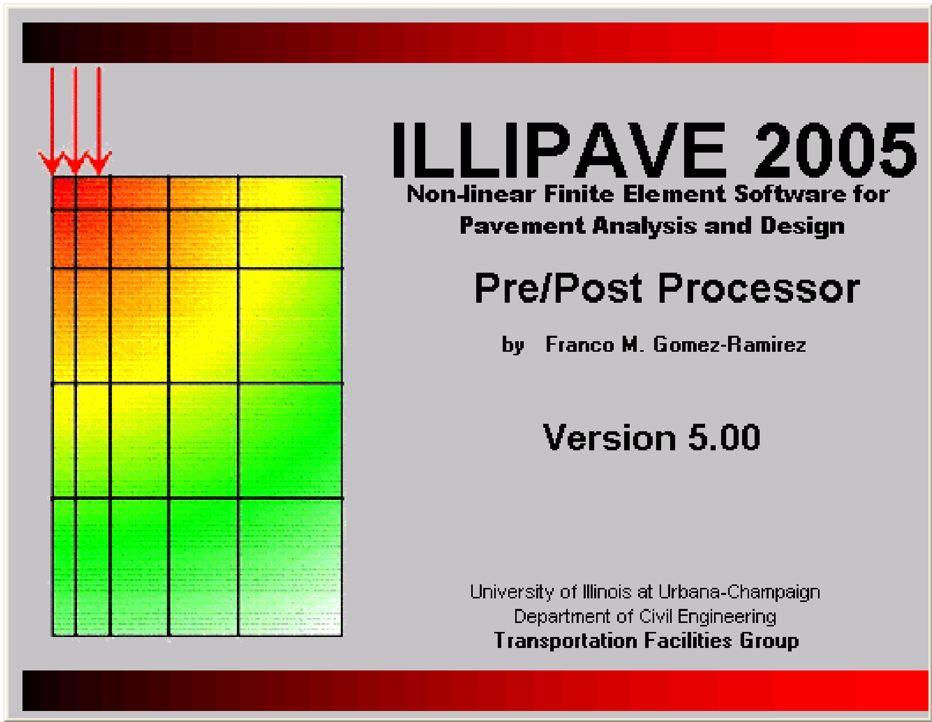
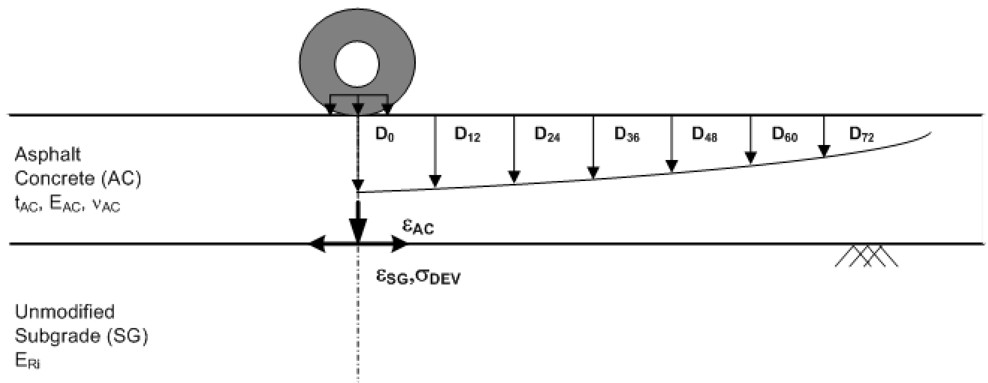


Figure 3-1. ILLIPAVE 2005 finite element software for pavement analysis.

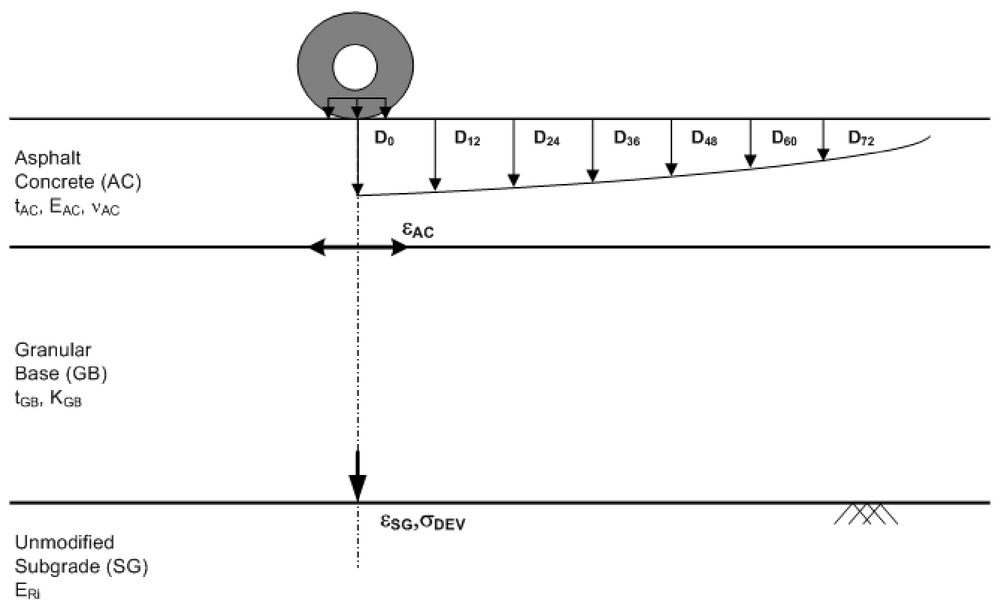
These deflections are in conformity with the uniform spacing commonly used in FWD testing by many state highway agencies including Illinois (Table 3.1). Typically, finer mesh spacing was used in the loaded area with the horizontal spacing adjusted according to the locations of the geophones used in FWD tests. In addition to the deflections, the critical pavement responses, i.e., horizontal strain at the bottom of AC layer (ε_{AC}), vertical strain at the top of the subgrade (ε_{SG}), and the vertical deviator stress on top of the subgrade (σ_{DEV}) directly at the centerline of the FWD loading, were also extracted from ILLI-PAVE results. Figures 3-2(a) to (d) show the locations of these responses obtained from different types of flexible pavements. These critical pavement responses play a crucial role in the context of mechanistic-empirical asphalt pavement design procedures as they directly relate to major failure mechanisms due to excessive fatigue cracking and rutting in the wheel paths.

Table 3.1. Falling Weight Deflectometer Sensor Spacing

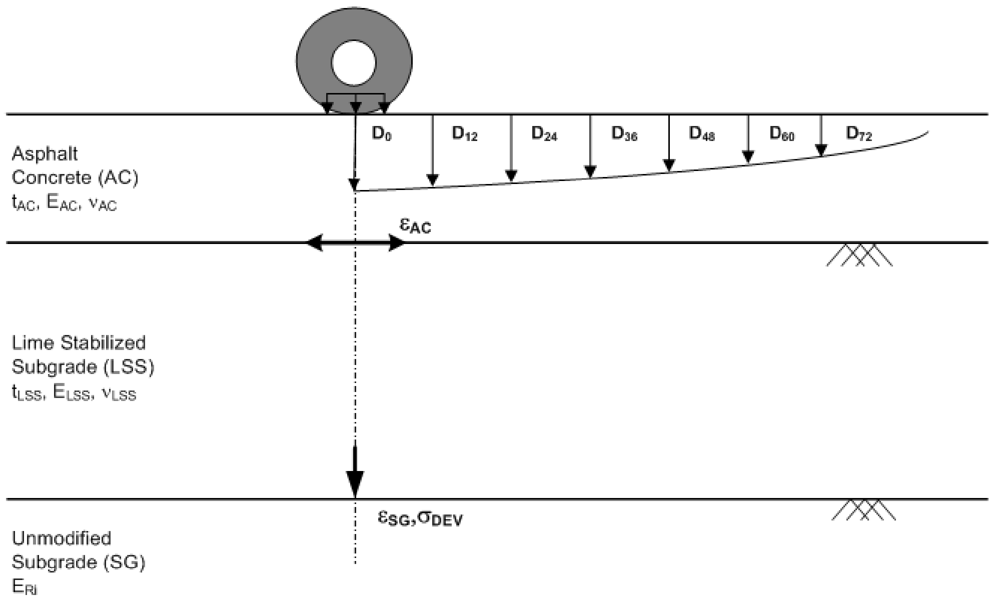
Sensor Spacing (in.)	0	8	12	18	24	36	48	60	72
Uniform (used in this study)	+		+		+	+	+	+	+
State Highway Research Program (SHRP)	+	+	+	+	+	+		+	



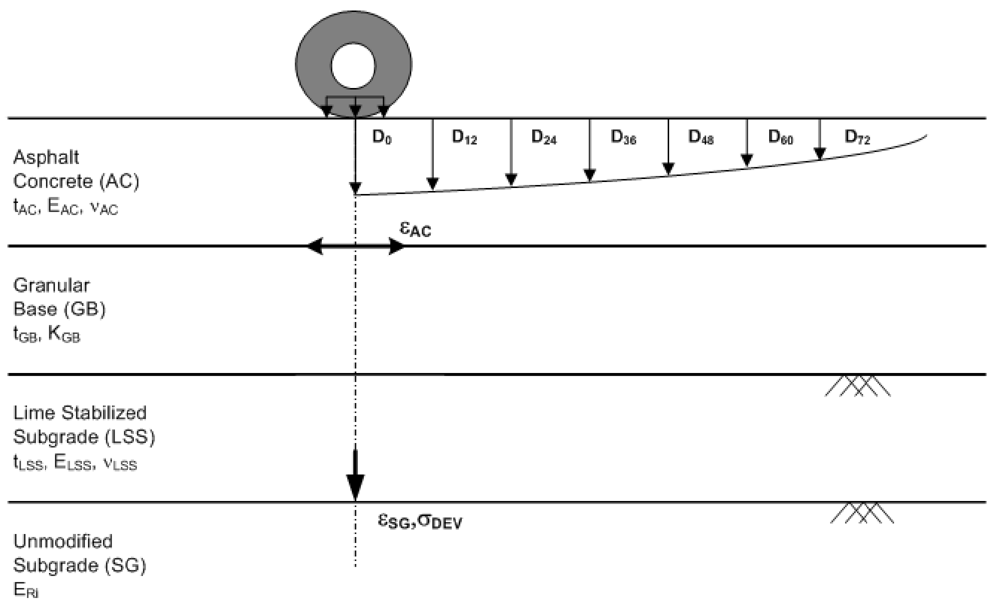
(a) full-depth asphalt pavements



(b) conventional flexible pavements



(c) full-depth asphalt pavements built on lime stabilized soils



(d) conventional flexible pavements built on lime stabilized soils

Figure 3-2. Locations of critical pavement responses and deflections.

A total analysis depth of 300 in. was selected for all pavements analyzed. Depending on the thicknesses of the layers, an aspect ratio of 1 was mainly used in the finite elements with a limiting value of 4 to get consistent pavement response predictions from ILLI-PAVE FE analyses (Pekcan et al. 2006). The vertical and horizontal spacings in the FE mesh were chosen appropriately so that there was neither numerical instability nor inconsistency in the results due to meshing. Figure 3-3 shows a sample ILLI-PAVE FE mesh that was used in the analyses of FDP-LSS. The thicknesses of all layers were selected to have appropriate ranges encountered for most flexible pavements in Illinois.

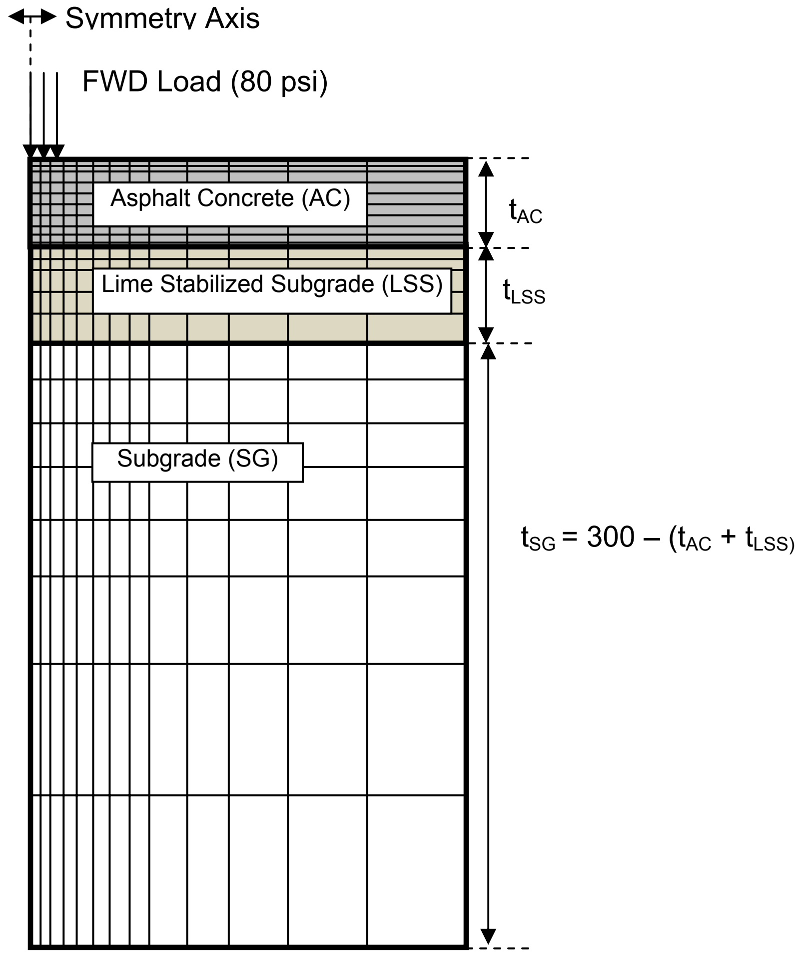


Figure 3-3. Finite element mesh for full-depth pavements on lime stabilized subgrade.

3.1.2 Pavement Layer Characterization

Adequately characterizing pavement layer behavior plays a crucial role for an accurate backcalculation of the layer moduli. Accordingly, modeling of FDP and CFP requires accurate material characterizations for the asphalt concrete, granular base and fine-grained subgrade soil layers. After material shakedown has taken place due to construction loading and early trafficking of the pavements, most of the deformations under a passing truck wheel are recoverable and hence considered resilient or elastic. The resilient modulus (M_R), defined by repeated wheel load stress divided by recoverable strain, is therefore the elastic modulus (E) often used to describe flexible pavement layer behavior under traffic loading.

In ILLI-PAVE FE models of the different flexible pavements analyzed, the asphalt concrete (AC) surface course was always represented with elastic properties, layer modulus E_{AC} and Poisson's Ratio ν_{AC}, for the instant loading during FWD testing. The value of ν_{AC} was taken constant as 0.35.

The modeling of fine-grained subgrade soils, mainly encountered in Illinois, has received more attention in the last three decades since it has a major impact on all the responses predicted under traffic loading within the context of M-E design. Fine-grained subgrade soils exhibit nonlinear behavior when subjected to traffic loading (Ceylan et al. 2005; Thompson and Robnett 1979). The subgrade stiffness characterized by the resilient modulus (M_R) is usually expressed as a function of the applied the deviator stress through nonlinear modulus response models. These models were developed based on the results of repeated load triaxial tests, which forms the basis of evaluating resilient properties of fine-grained soils (AASHTO-T307-99. 2000).

Illinois subgrade soils are mostly fine-grained, exhibit stress softening behavior, and can be characterized using the bilinear arithmetic model (Thompson and Elliott 1985; Thompson and Robnett 1979) with the modulus-deviator stress relationship shown in Figure 3-4. The upper limit deviator stress in the bilinear model, σ_{dul}, is dependent on the breakpoint modulus, E_{Ri}, which is also a function of the unconfined compressive strength, Q_u, expressed by Equation 3-1 (Thompson and Robnett 1979). E_{Ri} is a characteristic property of the fine-grained soil often computed for Illinois soils at a breakpoint deviator stress σ_{di} of 6 psi. The corresponding values and parameters of the bilinear model used in the analyses are also given in Figure 3-4.

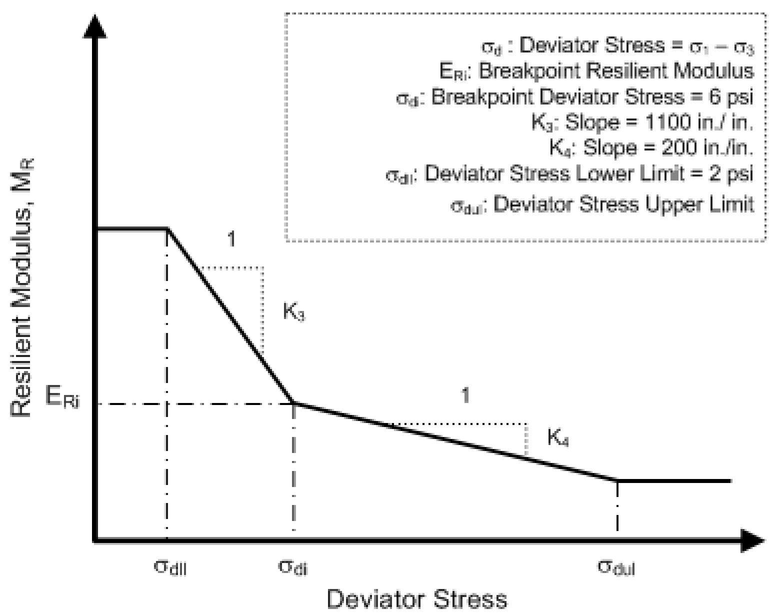


Figure 3-4. Bilinear model to characterize stress dependency of fine-grained soils.

$$\sigma_{dul}(psi) = Q_u(psi) = \frac{E_{RI} \cdot (ksi) - 0.86}{0.307} \qquad (3\text{-}1)$$

The granular base (GB) layer provides the essential load transfer in a conventional flexible pavement. The effect of this layer is predominant in determining the fatigue behavior of AC layer. The well known K-θ model (Hicks and Monismith 1971) was used in our modeling study to characterize the stress dependency of elastic, i.e., resilient, modulus in ILLI-PAVE analyses. In this model, the modulus stress dependency is considered by the use of two model parameters, “K” and “n”. The model parameter “n” is correlated to K-parameter according to Equation 3-2, where K is in psi. A major advantage of the given equation is that the unbound aggregate modulus characterization model then only requires one model parameter. K-θ model parameters of different granular materials (K and n values) are also given in Table 3.2. Typical "K" values range from 3 ksi to 12 ksi based on the comprehensive granular material database compiled by Rada and Witczak (1981) (Figure 3-5). Poisson's ratio was taken as 0.35 when K ≥ 5 ksi otherwise it was assumed 0.40.

$$\log_{10}(K) = 4.657 - 1.807 * n \tag{3-2}$$

Table 3.2. Typical Resilient Property Data for Granular Materials (after Rada and Witczak 1981)

Granular Material Type	Number of Data Points	K (psi) *		n *	
		Mean	Standard Deviation	Mean	Standard Deviation
Silty Sands	8	1620	780	0.62	0.13
Sand-Gravel	37	4480	4300	0.53	0.17
Sand-Aggregate Blends	78	4350	2630	0.59	0.13
Crushed Stone	115	7210	7490	0.45	0.23

* $E_R = K\theta^n$ where E_R is Resilient modulus and K, n are model parameters obtained from multiple regression analyses of repeated load triaxial test data.

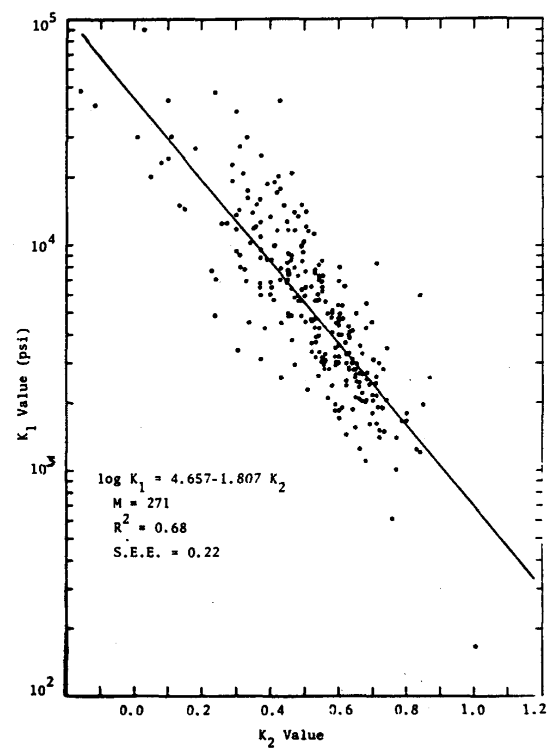


Figure 3-5. Relationship between K (shown as K1) and n (shown as K2) values for granular materials identified by Rada and Witczak (1981).

3.2 LIME STABILIZATION

Pavement design and performance requirements often necessitate the use of a treated subgrade when pavements are to be constructed on soft and weak subgrade soils. Lime stabilization is commonly utilized for this purpose as an effective and inexpensive ground improvement technique in the area of transportation geotechnics. Application of lime, especially in clayey soils, results in a major improvement in the strength and deformation characteristics. Moreover, it significantly improves the long term moisture and rutting susceptibilities of fine-grained soils while also providing a working platform and the needed expediency in the construction of transportation facilities (TRB 1987). Lime stabilization helps control the stiffness variability in soil layers, which is one of the most challenging problems in numerical modeling of geomaterials (Haussman 1990). Various geotechnical applications can be found in the literature (Moseley and Kirsch 2004). Its improvement effects on the engineering properties of fine-grained soils or the fine portion of granular soils facilitate the use of the lime-stabilized subgrade (LSS) as modified pavement layers. The lime stabilization of clayey subgrade soils has been a popular stabilization technique in the state of Illinois.

In Illinois, the existence and added performance of a lime stabilized subgrade (LSS) is usually ignored in pavement design and field evaluation. This is because the LSS is often constructed to establish a stable working platform for the construction equipment and not directly considered as an improved structural layer coefficient in the design of pavements (Little 1999). Even though it is not taken into account in pavement design, the long term effect of LSS in the pavement structure is certainly reflected in the FWD deflection basins to affect the backcalculated layer properties. A proper ANN backcalculation model, should therefore consider the contribution of LSS layer to measured FWD deflection basins and pavement performance.

Although soil-lime reactions are complex considering the generalized compressive stress-strain relations for cured and uncured soil-lime mixtures (Little 1999; TRB 1987), in ILLI-PAVE FE analyses, it was assumed that LSS layer exhibited linear elastic behavior. Figure 3-6 shows the effect of lime on vertical compressive stress-strain responses of fine grained subgrade soils (Thompson 1966). Figure 3-7 shows the effect of lime stabilization on stress-strain characteristics that occur without curing (Neubauer and Thompson 1972). Figure 3-8(a) and (b) show the immediate effects of lime treatment on soils compacted at the wet side of optimum moisture contents (McDonald 1969). Figure 3.9 shows a generalized stress-strain curve developed as a result of an extensive study of Illinois soils stabilized with lime (Thompson 1966). In summary, the reviewed studies provided adequate support for modeling the LSS layer using elastic layer properties E_{LSS} and ν_{LSS}. The value of ν_{LSS} was selected to be 0.31 and remained constant with stress levels (TRB 1987).

3.2.1 Preliminary Analyses of Lime Stabilized Sections

The contributions of an existing LSS layer and the nonlinear behavior of underlying subgrade on FWD deflection profiles and pavement response predictions might inherently be modeled using ANNs. The main objective of this section is therefore to prove that lime stabilization has a definite impact on pavement performance for flexible pavements including full-depth asphalt pavements (FDPs) and conventional flexible pavements (CFPs). Then, ANN based models can be developed for backcalculation and forward analyses of flexible pavements including full-depth asphalt pavements on lime stabilized subgrade (FDPs-LSS) and conventional flexible pavements on lime stabilized subgrade (CFPs-LSS). Proper quantification of the improvement in pavement responses, i.e., deflections, strains, and stresses, due to LSS is necessary to facilitate comparisons between FDP vs. FDP-LSS and

CFP vs. CFP-LSS solutions. This is achieved in this section through FE modeling of both pavement types and comparing the analysis results.

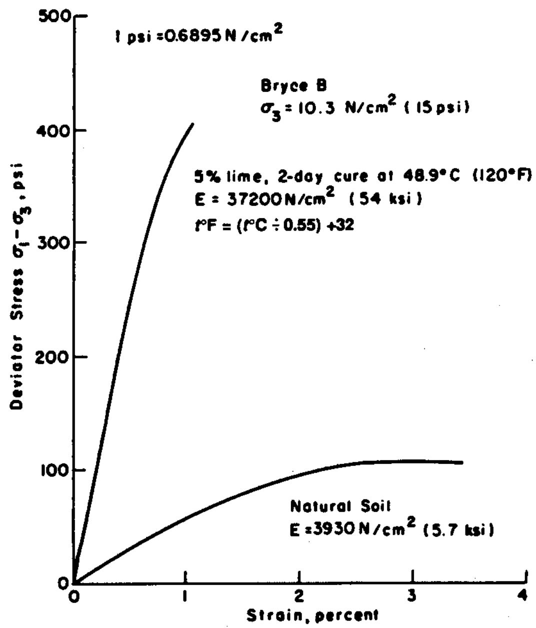


Figure 3.6. Typical stress – strain curves for natural and lime treated soils (TRB 1987).

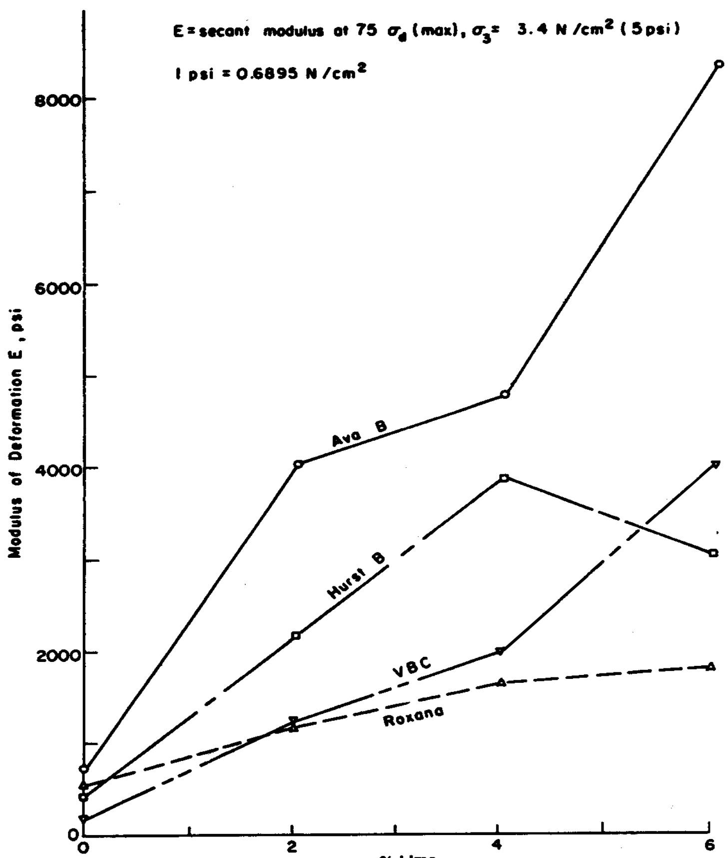


Figure 3.7. Immediate effects of lime treatment without curing on modulus deformation (Neubauer and Thompson 1972).

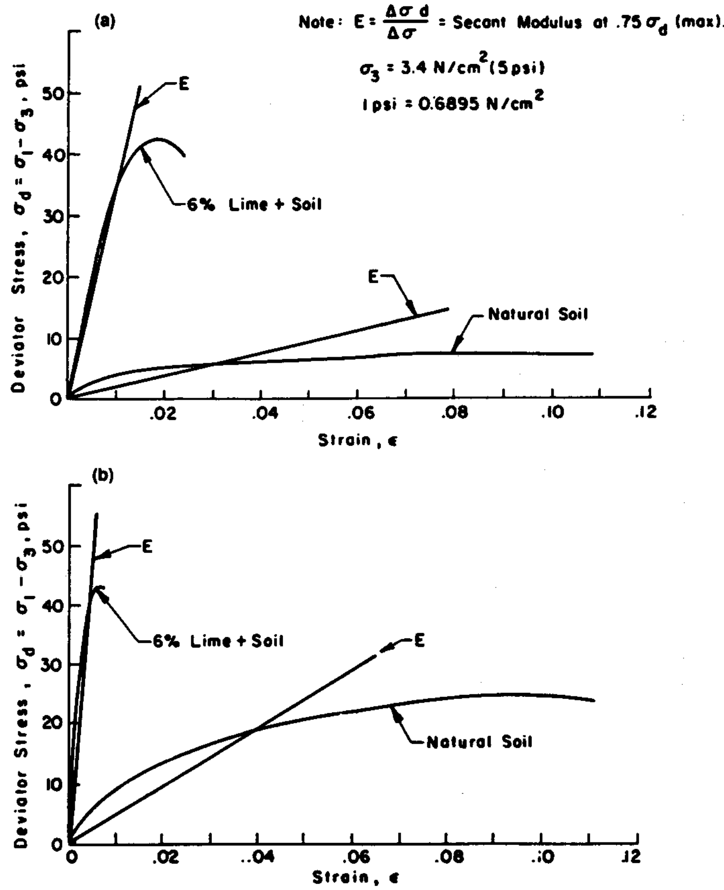


Figure 3-8. a. Typical stress–strain curves for immediate effects of lime treatment (a)Vicksburg buckshot clay (b)Ava B. (McDonald 1969).

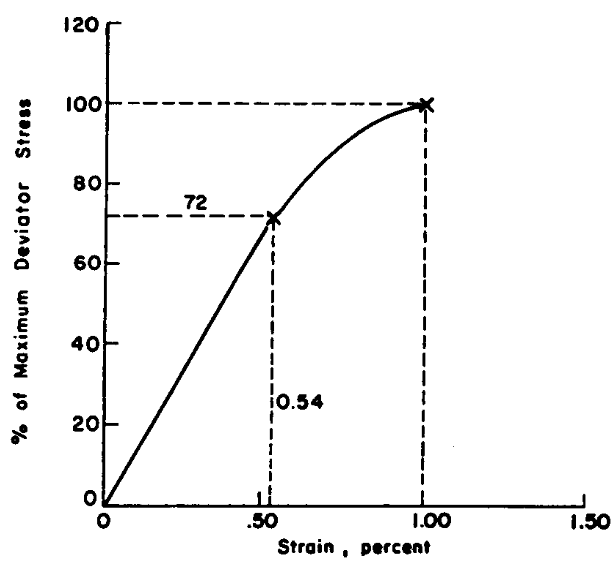


Figure 3-9. Generalized stress strain relationship for cured soil-lime mixtures (Thompson 1966).

3.2.1.1 Full-Depth Asphalt Pavements on Lime Stabilized Soils

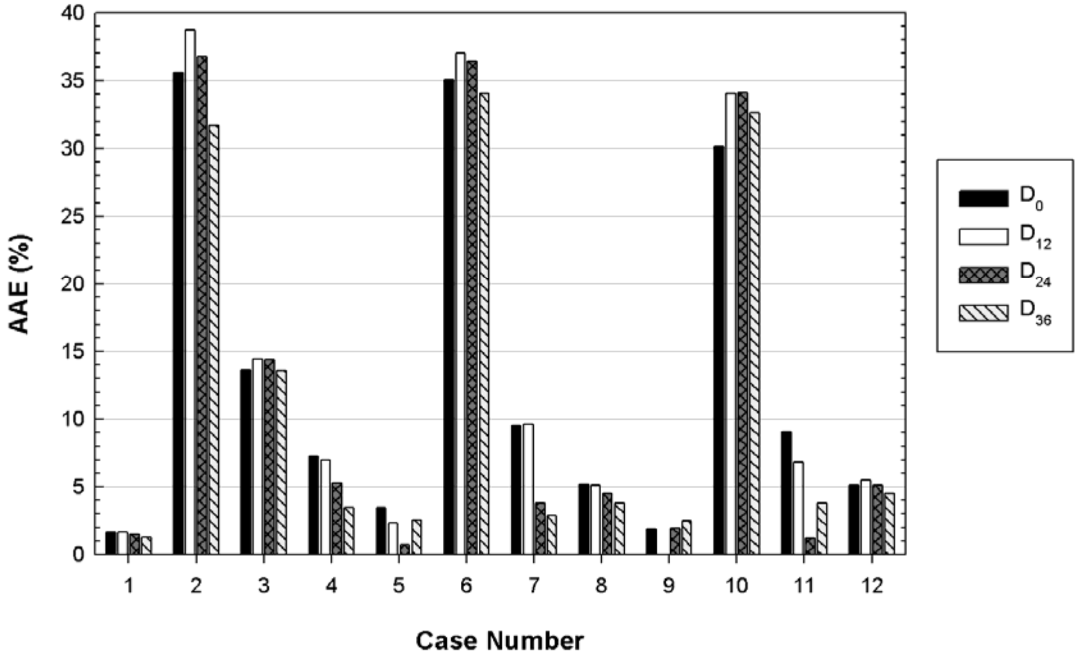
The motivation in this section was to investigate the differences in the FWD deflection profiles and predicted pavement responses, if any, between the FDPs and FDPs-LSS. In an effort to quantify these discrepancies in critical pavement responses and deflection values, ILLI-PAVE preliminary analyses were carried out for the typical ranges of layered pavement geometries and material properties (see Table 3.3). The ranges of inputs, i.e., the thickness of asphalt concrete layer (t_{AC}), the thickness of lime stabilized subgrade layer (t_{LSS}), E_{AC}, E_{LSS} and E_{Ri}, were carefully chosen to cover the most values of all FDPs-LSS found in Illinois. The depth of the untreated subgrade beneath the LSS layer was computed each time based on the total constant height of the FE analysis mesh. The similar FDP sections having the same properties but with no LSS were also analyzed using the ILLI-PAVE FE program.

Table 3.3. Ranges of FDP-LSSs Studied in the ILLI-PAVE Preliminary Analyses

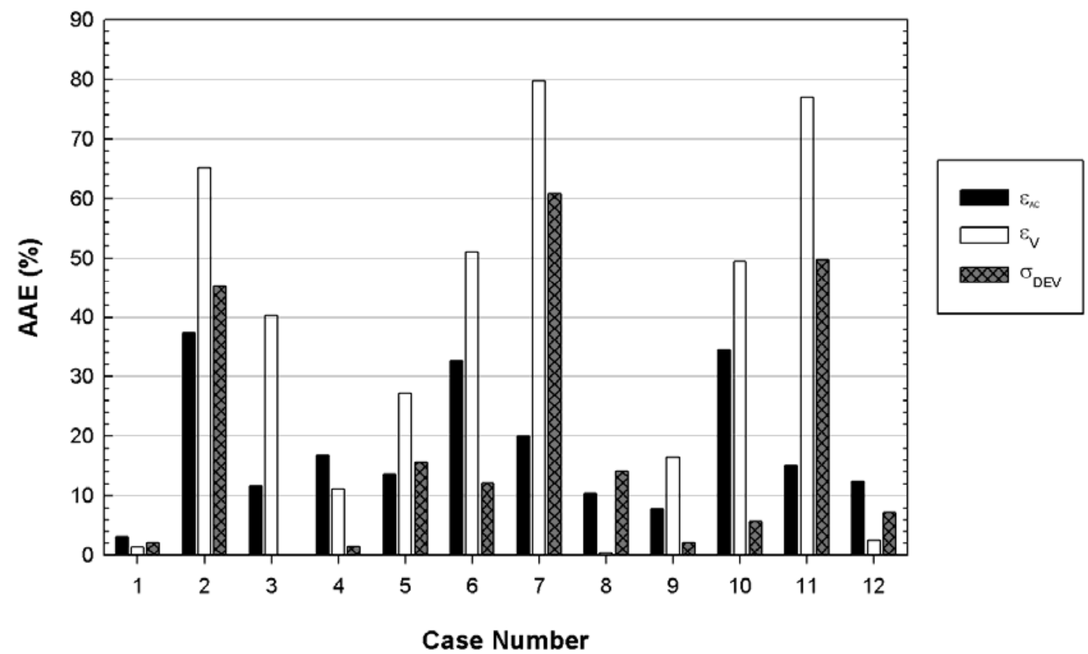
Case Number	t_{AC} (in.)	t_{LSS} (in.)	E_{AC} (psi)	E_{LSS} (psi)	E_{Ri} (psi)	Sensitivity Variable
1	9	4	1×10^6	1.5×10^4	1.0×10^3	E_{Ri}
2	9	22	1×10^6	1.0×10^5	1.4×10^4	
3	9	22	1×10^6	1.5×10^4	1.0×10^3	
4	9	4	1×10^6	1.0×10^5	1.4×10^4	
5	9	4	1×10^5	1.5×10^4	7.5×10^3	E_{AC}
6	9	22	2×10^6	1.0×10^5	7.5×10^3	
7	9	22	1×10^5	1.5×10^4	7.5×10^3	
8	9	4	2×10^6	1.0×10^5	7.5×10^3	
9	3	4	1×10^6	1.5×10^4	7.5×10^3	t_{AC}
10	15	22	1×10^6	1.0×10^5	7.5×10^3	
11	3	22	1×10^6	1.5×10^4	7.5×10^3	
12	15	4	1×10^6	1.0×10^5	7.5×10^3	

The results of preliminary ILLI-PAVE analyses are presented for both LSS and no lime pavements using the average absolute errors (AAEs) of deflection values and critical pavement responses in Figures 3-10(a) and (b), respectively. AAE is defined in Equation 3-3 where the measured value is the one obtained for FDP while the calculated one is for FDP-LSS.

$$Average\ Absolute\ Error\ (AAE) = \frac{\sum_{i=1}^{n} \left| (Measured_i - Calculated_i) / Measured_i \right|}{n} \times 100 \qquad (3\text{-}3)$$



(a) Deflection Basin Differences



(b) Critical Pavement Response Differences

Figure 3-10. ILLI-PAVE comparisons between FDP-LSS and FDP with no lime.

As shown in Figure 3-10(a), while the maximum AAE or difference in deflections can reach up to 39% for case 2, the total average difference for all deflection values is about 12%. Furthermore, in Figure 3-10(b), the total average differences for ε_{AC}, ε_{SG}, and σ_{DEV} are approximately 18%, 18%, and 35%, respectively. This is in spite of the fact that, the maximum differences can reach up to 38%, 60%, and 80% for ε_{AC}, ε_{SG}, and σ_{DEV}, respectively. Therefore, the placement of lime stabilized layer over the untreated subgrade considerably changed the overall responses of FDPs. Almost up to 40% differences in the deflection values certainly affect the accuracy of backcalculated layer moduli from the FWD deflection basins.

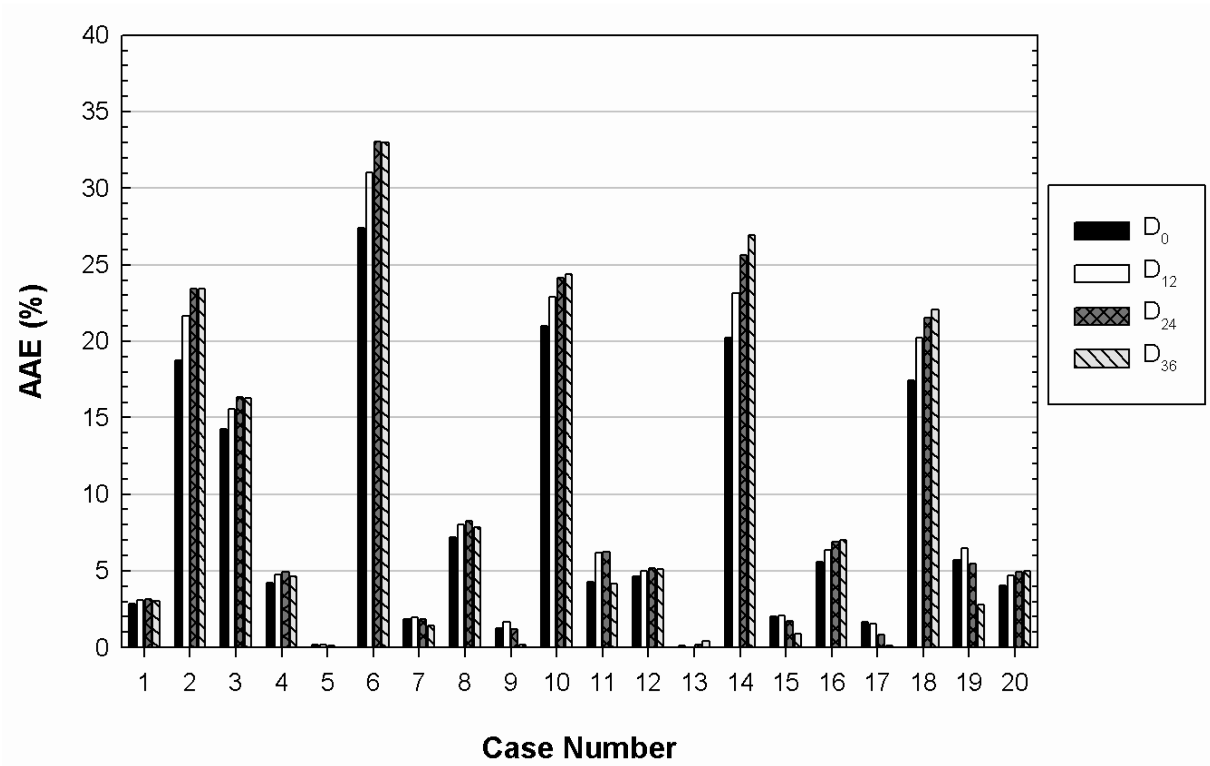
3.2.1.2 Conventional Flexible Pavements on Lime Stabilized Soils

To show the additional effect of lime stabilized soil layer on critical pavement responses and deflection profiles for conventional flexible pavements, preliminary analyses were also needed. For this purpose, 20 different CFP-LSS sections were analyzed using the ILLI-PAVE FE program under the typical 9-kip FWD loading. The inputs were selected such that they included extensive ranges of material properties and thicknesses (see Table 3.4). The lime-stabilized soil layer was then replaced with natural subgrade and the analyses were repeated. This way, CFP and CFP-LSS critical pavement responses could be compared effectively. The deflection profiles and critical pavement responses from the preliminary analyses are compared again using the computed average absolute errors (AAE), defined in Equation 3-3 where the measured value is the one obtained for CFP while the calculated one is for CFP-LSS.

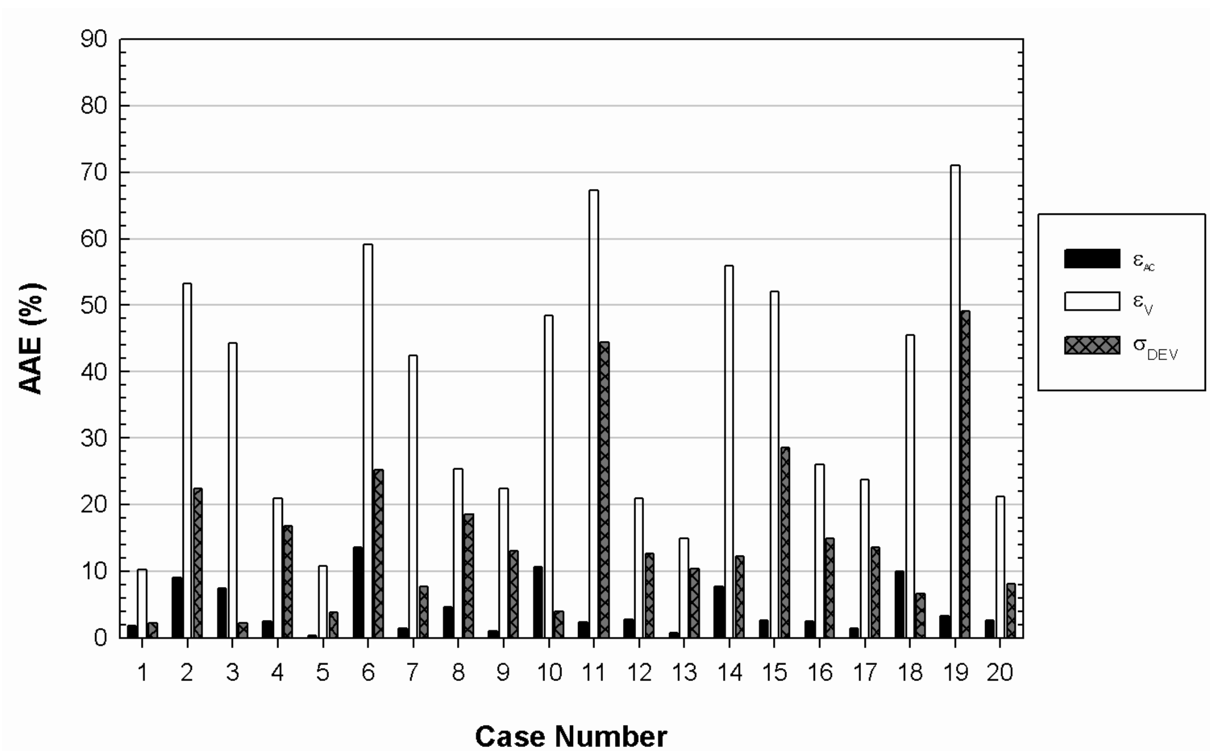
The results are presented in Figures 3-11(a) and (b). The maximum AAE in deflection values (see Figure 3-11a) is observed to be 33% (Case 6) and the average of all deflection AAE values is calculated as 9%. The comparisons of critical pavement response, however, indicated higher variations. While the maximum AAE values for ε_{AC}, ε_{SG}, and σ_{DEV} can reach up to 14% (Case 6), 71% (Case 19) and 49% (Case 19), respectively, the average AAE values are calculated as 4%, 37% and 16%, for ε_{AC}, ε_{SG}, and σ_{DEV}, respectively (see Figure 3-11b). Hence, accurate pavement responses could not be computed by neglecting the contribution of the LSS layer.

Table 3.4. Ranges of CFP-LSS Material Properties Used in The Preliminary Analyses

Case Number	t_{AC} (in.)	t_{GB} (in.)	t_{LSS} (in.)	E_{AC} (psi)	K_{GB} (psi)	E_{LSS} (psi)	E_{Ri} (psi)	Sensitivity Variable
1	9	13	4	1.0×10^6	7.5×10^3	1.5×10^4	1.0×10^3	E_{Ri}
2	9	13	22	1.0×10^6	7.5×10^3	1.0×10^5	1.4×10^4	
3	9	13	22	1.0×10^6	7.5×10^3	1.5×10^4	1.0×10^3	
4	9	13	4	1.0×10^6	7.5×10^3	1.0×10^5	1.4×10^4	
5	9	13	4	1.0×10^6	3.0×10^3	1.5×10^4	7.5×10^3	K_{GB}
6	9	13	22	1.0×10^6	1.2×10^4	1.0×10^5	7.5×10^3	
7	9	13	22	1.0×10^6	3.0×10^3	1.5×10^4	7.5×10^3	
8	9	13	4	1.0×10^6	1.2×10^4	1.0×10^5	7.5×10^3	
9	9	13	4	1.0×10^5	7.5×10^3	1.5×10^4	7.5×10^3	E_{AC}
10	9	13	22	2.0×10^6	7.5×10^3	1.0×10^5	7.5×10^3	
11	9	13	22	1.0×10^5	7.5×10^3	1.5×10^4	7.5×10^3	
12	9	13	4	2.0×10^6	7.5×10^3	1.0×10^5	7.5×10^3	
13	9	4	4	1.0×10^6	7.5×10^3	1.5×10^4	7.5×10^3	t_{GB}
14	9	22	22	1.0×10^6	7.5×10^3	1.0×10^5	7.5×10^3	
15	9	4	22	1.0×10^6	7.5×10^3	1.5×10^4	7.5×10^3	
16	9	22	4	1.0×10^6	7.5×10^3	1.0×10^5	7.5×10^3	
17	3	13	4	1.0×10^6	7.5×10^3	1.5×10^4	7.5×10^3	t_{AC}
18	15	13	22	1.0×10^6	7.5×10^3	1.0×10^5	7.5×10^3	
19	3	13	22	1.0×10^6	7.5×10^3	1.5×10^4	7.5×10^3	
20	15	13	4	1.0×10^6	7.5×10^3	1.0×10^5	7.5×10^3	



(a) Deflection Basin Differences

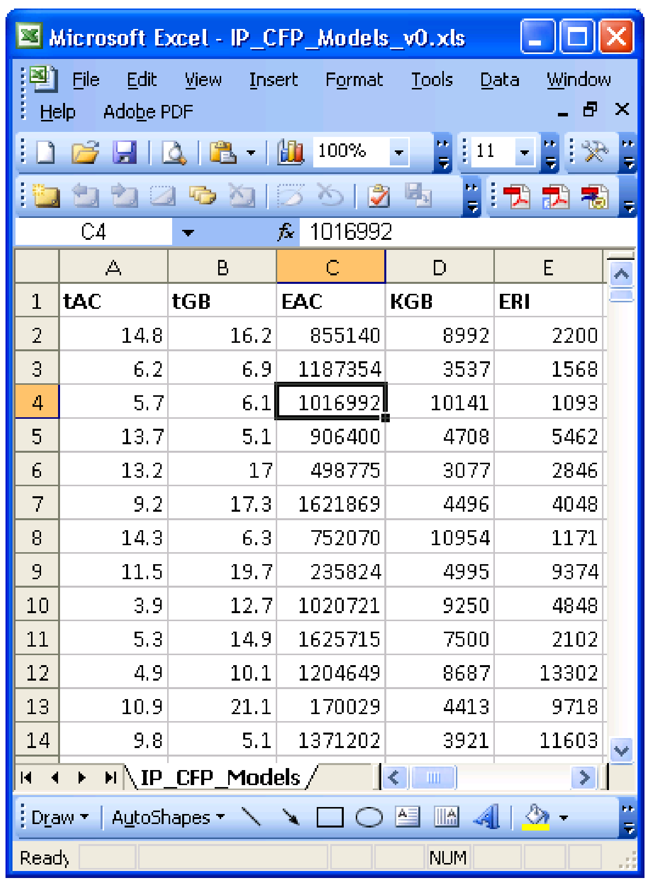


(b) Critical Pavement Response Differences

Figure 3-11. ILLI-PAVE Comparisons between CFP-LSS and CFP with no lime.

3.3 ILLI-PAVE DATABASE FOR FLEXIBLE PAVEMENTS

Randomly selected combinations of material and thickness inputs were provided to ILLI-PAVE to generate batch analyses. For this purpose, a M.S. Excel file was created for a given pavement to list in it the thickness of asphalt concrete (t_{AC}), thickness of unbound aggregate base (t_{GB}), modulus of AC layer (E_{AC}), K parameter for granular base model (K_{GB}), and the breakpoint deviator stress (E_{Ri}) for fine grained soil randomly chosen in the predefined ranges of properties for Conventional Flexible Pavements (see Figure 3-12). A batch program interface was written in Borland Delphi (see Figure 3-13) capable of producing ILLI-PAVE input files with the material and thickness properties obtained from the corresponding M.S. Excel file. This software mainly duplicates ILLI-PAVE preprocessor which was written using M.S. Visual Basic and is available to the researchers. By using this new software program, named ILLI-PAVE auto analysis, numerous runs were made to cover the whole ranges of layer moduli and thicknesses as illustrated in Figure 3-14. Also developed using Borland Delphi, ILLI-PAVE auto analysis completely replaces the analysis engine embedded in ILLI-PAVE 2005 and is capable of extracting the deflections and critical pavement responses from the analyses to form a database consisting of inputs and outputs of the flexible pavement analyses (see Figure 3-15). This database, which inherently captured the nonlinear FE approximations, was then used to train and develop an ANN-based structural analysis toolbox containing several ANN models for forward and backcalculation analyses of flexible pavements.



	A	B	C	D	E
1	tAC	tGB	EAC	KGB	ERI
2	14.8	16.2	855140	8992	2200
3	6.2	6.9	1187354	3537	1568
4	5.7	6.1	1016992	10141	1093
5	13.7	5.1	906400	4708	5462
6	13.2	17	498775	3077	2846
7	9.2	17.3	1621869	4496	4048
8	14.3	6.3	752070	10954	1171
9	11.5	19.7	235824	4995	9374
10	3.9	12.7	1020721	9250	4848
11	5.3	14.9	1625715	7500	2102
12	4.9	10.1	1204649	8687	13302
13	10.9	21.1	170029	4413	9718
14	9.8	5.1	1371202	3921	11603

Figure 3-12. Randomly selected inputs shown in an M.S. Excel file for ILLI-PAVE analyses.

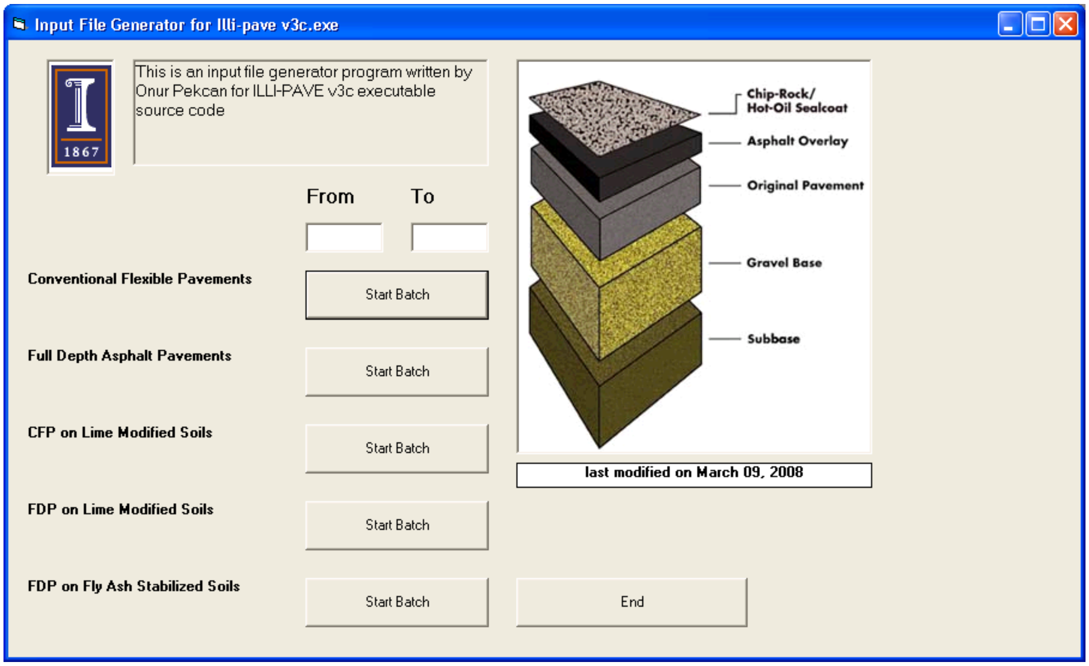


Figure 3-13. ILLI-PAVE input data generator.

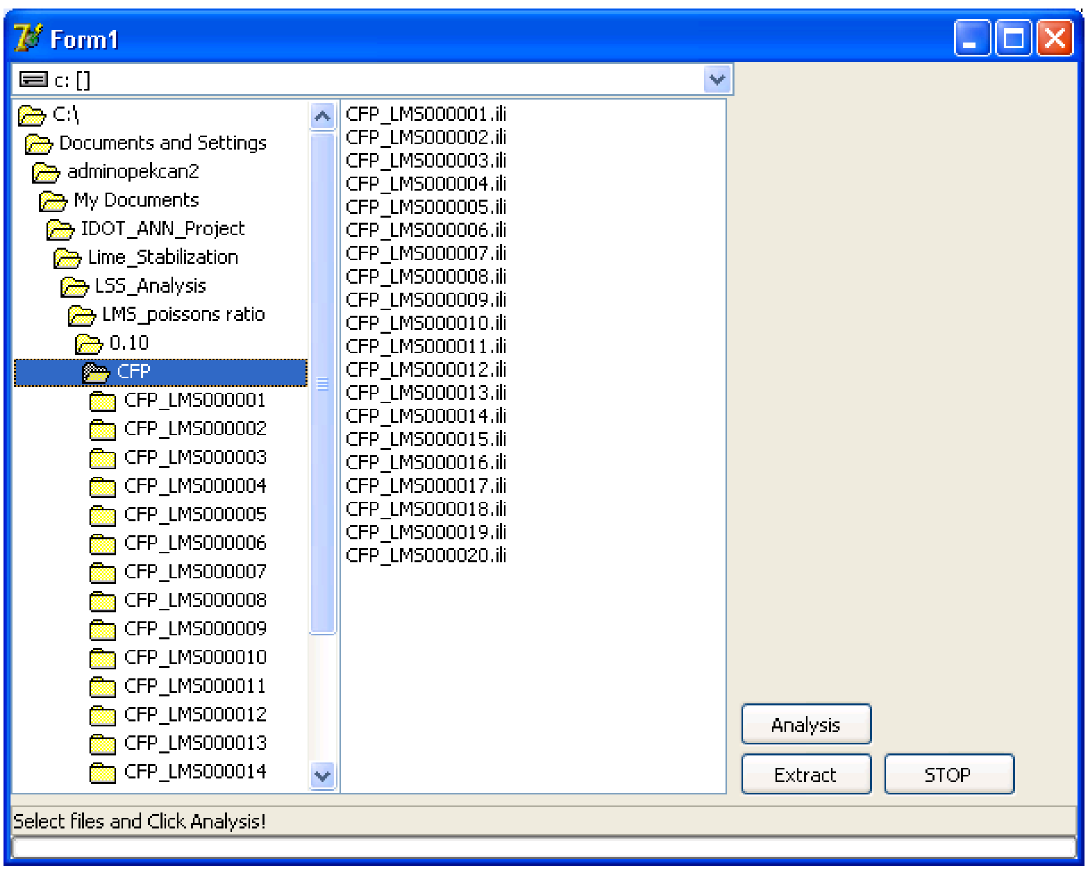
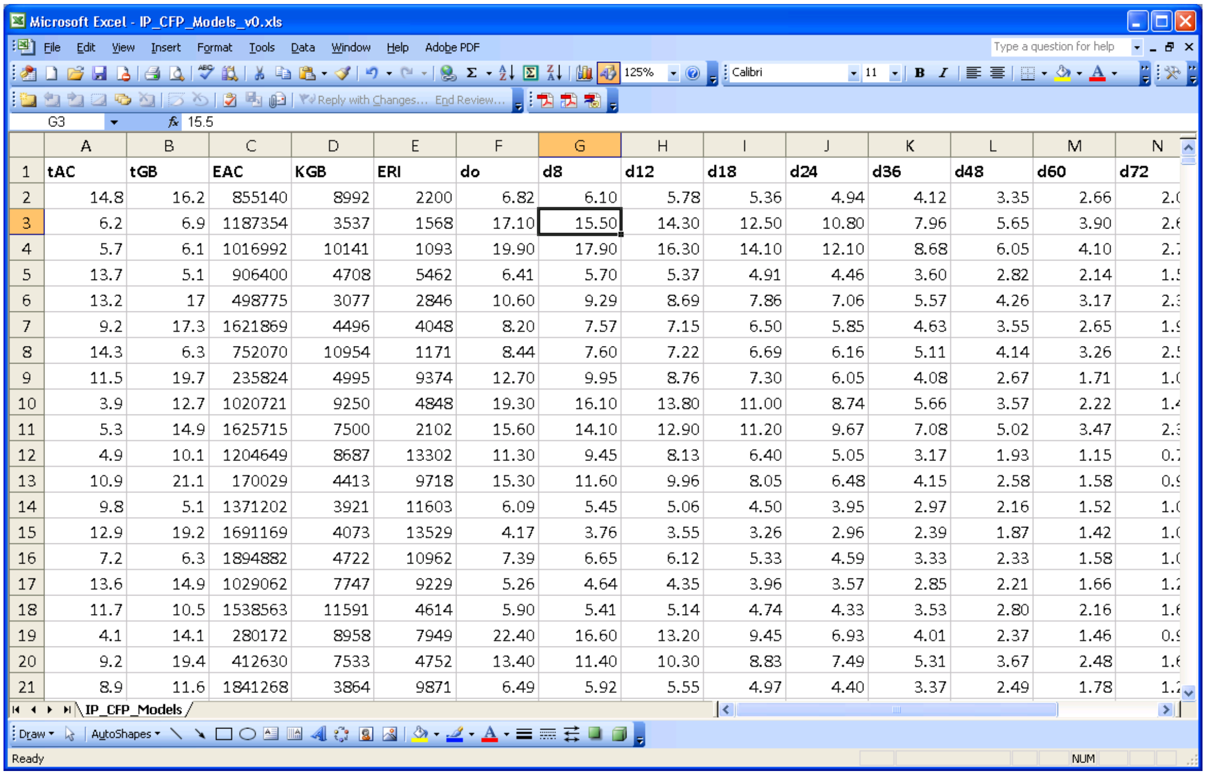


Figure 3-14. ILLI-PAVE auto analysis engine.



	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	tAC	tGB	EAC	KGB	ERI	do	d8	d12	d18	d24	d36	d48	d60	d72
2	14.8	16.2	855140	8992	2200	6.82	6.10	5.78	5.36	4.94	4.12	3.35	2.66	2.0
3	6.2	6.9	1187354	3537	1568	17.10	15.50	14.30	12.50	10.80	7.96	5.65	3.90	2.6
4	5.7	6.1	1016992	10141	1093	19.90	17.90	16.30	14.10	12.10	8.68	6.05	4.10	2.7
5	13.7	5.1	906400	4708	5462	6.41	5.70	5.37	4.91	4.46	3.60	2.82	2.14	1.5
6	13.2	17	498775	3077	2846	10.60	9.29	8.69	7.86	7.06	5.57	4.26	3.17	2.3
7	9.2	17.3	1621869	4496	4048	8.20	7.57	7.15	6.50	5.85	4.63	3.55	2.65	1.9
8	14.3	6.3	752070	10954	1171	8.44	7.60	7.22	6.69	6.16	5.11	4.14	3.26	2.5
9	11.5	19.7	235824	4995	9374	12.70	9.95	8.76	7.30	6.05	4.08	2.67	1.71	1.0
10	3.9	12.7	1020721	9250	4848	19.30	16.10	13.80	11.00	8.74	5.66	3.57	2.22	1.4
11	5.3	14.9	1625715	7500	2102	15.60	14.10	12.90	11.20	9.67	7.08	5.02	3.47	2.3
12	4.9	10.1	1204649	8687	13302	11.30	9.45	8.13	6.40	5.05	3.17	1.93	1.15	0.7
13	10.9	21.1	170029	4413	9718	15.30	11.60	9.96	8.05	6.48	4.15	2.58	1.58	0.9
14	9.8	5.1	1371202	3921	11603	6.09	5.45	5.06	4.50	3.95	2.97	2.16	1.52	1.0
15	12.9	19.2	1691169	4073	13529	4.17	3.76	3.55	3.26	2.96	2.39	1.87	1.42	1.0
16	7.2	6.3	1894882	4722	10962	7.39	6.65	6.12	5.33	4.59	3.33	2.33	1.58	1.0
17	13.6	14.9	1029062	7747	9229	5.26	4.64	4.35	3.96	3.57	2.85	2.21	1.66	1.2
18	11.7	10.5	1538563	11591	4614	5.90	5.41	5.14	4.74	4.33	3.53	2.80	2.16	1.6
19	4.1	14.1	280172	8958	7949	22.40	16.60	13.20	9.45	6.93	4.01	2.37	1.46	0.9
20	9.2	19.4	412630	7533	4752	13.40	11.40	10.30	8.83	7.49	5.31	3.67	2.48	1.6
21	8.9	11.6	1841268	3864	9871	6.49	5.92	5.55	4.97	4.40	3.37	2.49	1.78	1.2

Figure 3-15. Sample M.S. Excel database used to train ANN models.

The input files for ILLI-PAVE FE analyses were generated by randomly selecting values for each of the thickness and moduli combinations for different types of flexible pavements. A total of 24,000 ILLI-PAVE runs were made for FDP and 24,100 for CFP in order to fully cover the material property ranges given in Tables 3.5 and 3.6. The surface deflections corresponding to the locations of the FWD sensors and the critical pavement responses, i.e., horizontal strain at the bottom of AC layer (ε_{AC}), vertical strain at the top of the subgrade (ε_{SG}), and the deviator stress on top of the subgrade (σ_{DEV}), directly at the centerline of the FWD loading were then extracted from the ILLI-PAVE output files.

Table 3.5. Geometries and Material Properties of Full-Depth Flexible Pavements Analyzed

Material Type	Thickness (in.)	Material Model	Elasticity Modulus (ksi)	Poisson's Ratio
Asphalt Concrete (AC)	5-24	Linear Elastic	100 – 2 000	0.35
Fine Grained Subgrade (SG)	(300- t_{AC})	Nonlinear Bilinear Model	1-14	0.45

Table 3.6. Geometries and Material Properties of Conventional Flexible Pavements Analyzed

Material Type	Thickness (in.)	Material Model	Elasticity Modulus (ksi)	Poisson's Ratio
Asphalt Concrete (AC)	5-24	Linear Elastic	100 – 2 000	0.35
Granular Base (GB)	4-22	Nonlinear K-θ model	3 - 12	0.35 for K ≥ 5 ksi 0.40 for K < 5 ksi
Fine Grained Subgrade (SG)	(300- t_{AC} – t_{GB})	Nonlinear Bilinear Model	1-14	0.45

The preliminary analyses proved that FDP-LSS pavements had to be analyzed separately to consider the contribution of lime stabilization and capture more accurate pavement responses for forward and backcalculation purposes. Sufficiently wide ranges of material and geometry properties of flexible pavements on LSS were analyzed to form a database for training ANNs to model the complex and nonlinear relations between the pavement properties and the responses. Table 3.7 lists the typical ranges of FDP-LSS pavement geometries and material properties selected to represent field conditions for establishing the ANN database. Totally 26,000 ILLI-PAVE analyses were performed to fully capture the ranges defined in Table 3-6. To make sure that ANN models had the ability to perform correctly for representative field conditions, the ranges of layer thickness values and material property inputs were extended up to ±20% beyond the actual field values. It was also guaranteed that training was done properly and poor performances of ANN models in the ranges of typical field conditions and thicknesses were prevented.

Table 3.7. Geometries and Material Properties of Full-Depth Flexible Pavements on Lime Stabilized Soils Analyzed

Material Type	Thickness (in.)	Material Model	Elasticity Modulus (ksi)	Poisson's Ratio
Asphalt Concrete (AC)	4-24	Linear Elastic	100 – 2 500	0.35
Lime Stabilized Subgrade (LSS)	4-20	Linear Elastic	16-150	0.31
Fine-grained Subgrade (SG)	(300- t_{AC} - t_{LSS})	Nonlinear Bilinear Model	1-15	0.45

The reported differences from preliminary analyses also confirmed that accuracy of FWD based backcalculated results for CFP-LSS could be improved when properly taking into account the LSS layer in the analyses. Therefore, CFP-LSS sections were analyzed under FWD loading with extensive ranges of material and geometry properties to develop an ILLI-PAVE finite element database. Critical pavement responses and deflection profiles were stored along with corresponding inputs. Typical ranges of CFP-LSS pavement geometries and material properties are given in Table 3.8. A total of 30,000 analyses were carried out with ILLI-PAVE to form the database. This database was also used for training of ANN models for the inverse pavement analysis or backcalculation.

Table 3.8. Geometries and Material Properties of Conventional Flexible Pavements on Lime Stabilized Soils Analyzed

Material Type	Thickness (in.)	Material Model	Layer Modulus Inputs (ksi)	Poisson's Ratio
Asphalt Concrete (AC)	3-18	Linear Elastic	100 – 2 500	0.35
Granular Base (GB)	4-22	Nonlinear K-θ model	3-16	0.35 for K ≥ 5 ksi 0.40 for K < 5 ksi
Lime Stabilized Subgrade (LSS)	4-20	Linear Elastic	16-150	0.31
Fine-grained Subgrade (SG)	(300- t_{AC} – t_{GB} - t_{LSS})	Nonlinear Bilinear Model	1-15	0.45

3.4 ANN STRUCTURAL MODELS

The multi-layered, feed-forward backpropagation type neural networks are mainly implemented for complex valued network level problems. In this project, backpropagation type ANNs were trained for the backcalculation of pavement layer moduli using the previously developed database with the input and output variables. Trained ANN models were tested based on an independent dataset within the ranges that they were trained. Approximately 1000 runs of all the datasets were independently and randomly chosen considering the given ranges of material and geometry properties and used as the testing datasets for the verification of proper ANN learning. The remaining ILLI-PAVE runs in the datasets were used for the training and/or learning task. The trained ANN models to determine whether or not they were capable of producing the same database results (with the given inputs to obtain outputs or vice versa) were checked quickly in this manner. Although training of each ANN model required a long computation time, with the already set weighted connections, testing was much faster (on the order of micro seconds). This advantage allows a field engineer to use trained ANN models as quick pavement analysis tools without the need for any complex inputs.

3.4.1. Forward Analysis Models

There are total of six ANN models designed to compute the responses of flexible pavements under a typical FWD loading. Two of them were developed for FDP and CFP pavements using the different geometries and layer properties. Although the input variables of these models are different by its nature, the outputs are the same for FDP-FW1 and CFP-

FW1 and they are given in Table 3-8. Both models were developed to predict the surface deflection values D_0, D_{12}, D_{24}, and D_{36} as well as critical pavement responses, i.e., ε_{AC}, ε_{SG}, σ_{DEV}. In addition, for both models, the ANN architectures were chosen to have two hidden layers with 60 neurons in each layer. This was according to the findings from similar ANN trainings performed by Ceylan et al. (2005). Finally, the ANN models were trained for 10,000 epochs.

Similar to FDP-FW1 and CFP-FW1, two different ANN models were developed to calculate the responses of FDP-LSS and CFP-LSS pavements using the different geometries and layer properties. The input and output variables of the ANN models are also given in Table 3.9. FDP-LSS-FW1 and CFP-LSS-FW1 models were developed to predict the surface deflection values D_0, D_{12}, D_{24}, and D_{36} using design thicknesses t_{AC} ,t_{LSS} and t_{GB} (see Table 3.9). Since it is often not desirable to have one ANN model to predict several different outputs at once – the prediction ability of the ANN model is negatively impacted when nonlinear mapping is done for too many output variables in one model – FDP-LSS-FW2 and CFP-LSS-FW2 models were also developed to predict this time the critical pavement responses using the same inputs. For all the models, the ANN architectures were chosen to have two hidden layers with 20 neurons in each layer. This was according to the findings from similar ANN trainings performed by Ceylan et al. (2005). The ANN models were trained for 10,000 epochs.

One of the basic advantages of the developed ANN models is that they do not require complicated FE inputs that are either difficult or costly to obtain through laboratory and field characterizations for the analyses of flexible pavements. Yet, the solutions are still considering the needed sophistication in analysis, such as, the stress dependent subgrade behavior and the lime-stabilized subgrade layer as an addition layer on top of the natural unmodified grade, and the realistic layered pavement structure of flexible pavements.

Table 3.9. Forward Artificial Neural Network Models for Flexible Pavements

Type	Inputs	Outputs
FDP-FW1	t_{AC},E_{AC}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}, ε_{AC}, ε_{SG},σ_{DEV}
CFP-FW1	t_{AC}, t_{GB}, E_{AC}, K_{GB}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}, ε_{AC}, ε_{SG},σ_{DEV}
FDP-LSS-FW1	t_{AC}, t_{LSS}, E_{AC}, E_{LSS}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}
FDP-LSS-FW2	t_{AC}, t_{LSS}, E_{AC}, E_{LSS}, E_{RI}	ε_{AC}, ε_{SG},σ_{DEV}
CFP-LSS-FW1	t_{AC}, t_{GB}, t_{LSS}, E_{AC}, K_{GB} ,E_{LSS}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}
CFP-LSS-FW2	t_{AC}, t_{GB}, t_{LSS}, E_{AC}, K_{GB} ,E_{LSS}, E_{RI}	ε_{AC}, ε_{SG},σ_{DEV}

3.4.1.1 Performances of the Developed ANN Models

ANN forward calculation models developed for the analyses of flexible pavements were verified for satisfactory performances using the independent testing data extracted from the database of the ILLI-PAVE FE solutions. The performances of ANN models were indicated by comparing predictions with the ILLI-PAVE FE results using average absolute error (AAE) values. Figure 3-16 shows the deflections predicted by ANN models at the FWD geophone locations D_0, D_{12}, D_{24}, and D_{36} to match very accurately with the ILLI-PAVE results with the given AAE values between 0.2 to 0.5%. The strains (ε_{AC} and ε_{SG}) predicted using ANNs vary on the average by only 2.0% while the subgrade deviator stresses σ_{DEV} predicted change on the average by 1.4% from the ILLI-PAVE FE analysis results (see Figure 3-17).

The results for CFPs are given in Figures 3-18 and 3-19 from the ANN model CFP-FW1. This model could predict the surface deflection values with an AAE value of at most 0.3%. Similarly, it was also successful in predicting the critical pavement responses ε_{AC}, ε_{SG}, and σ_{DEV} with AAE values of 0.5%, 0.8%, and 1.8%, respectively. The results proved that very good agreement was achieved when trying to replace ILLI-PAVE solutions with ANN predictions.

Figure 3-20 shows the deflection values predicted using the ANN model FDP-LSS-FW1. Comparisons with ILLI-PAVE results produced AAE values between 0.2 to 0.4% with a maximum error of 1.4%. Figure 3-21 also indicates that the strains ε_{AC} and ε_{SG} predicted using ANNs vary on the average by only 0.9% and 1.0%, respectively. On the other hand, the deviator stresses σ_{DEV} predicted on the unmodified subgrade change on the average by 1.5% from the ILLI-PAVE FE analysis results. Even the largest error computed for the subgrade deviator stress corresponds to within 0.1 psi, which is a negligibly small value for all practical engineering design applications with the developed ANN models. This is especially important when considering up to 40% differences in predicted responses computed earlier between the FDP solutions with and without lime.

The ANN model predictions for CFP-LSS are given in Figures 3-22 and 3-23 for Models CFP-LSS-FW1 and CFP-LSS-FW2, respectively. Model FW-1 could predict the surface deflection values with an AAE value of at most 0.4%. For example, this error accounts for ± 0.05 mils in D_0. Similarly, Model FW-2 was successful in predicting the critical pavement responses ε_{AC}, ε_{SG}, and σ_{DEV} with AAE values of 0.9%, 1.5%, and 1.0%, respectively. Therefore, these results once again have proven that very good agreement could be achieved when trying to replace ILLI-PAVE FE solutions with ANN model predictions. In addition, the developed ANN models eliminated the need for complex FE inputs that are usually not easy to determine in the laboratory or in the field. Consequently, these ANN models can be used successfully for practical structural analyses of pavements. All of the developed ANN forward calculation models were embedded in the Artificial Neural Network for Professionals software (ANN-Pro v1.0).

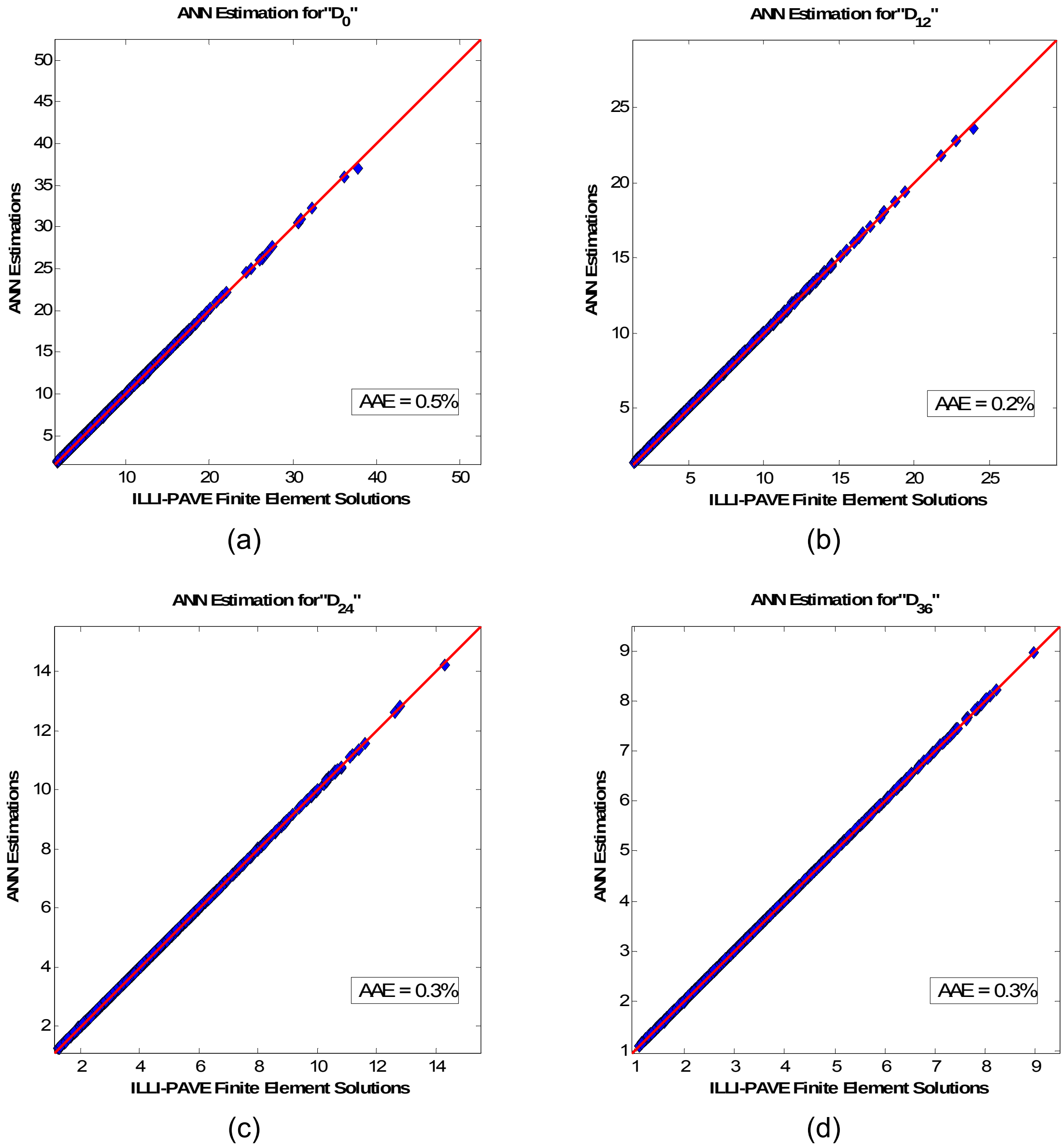


Figure 3-16. Comparisons of ANN structural model predictions with ILLI-PAVE results for full-depth asphalt pavement surface deflections (in mils).

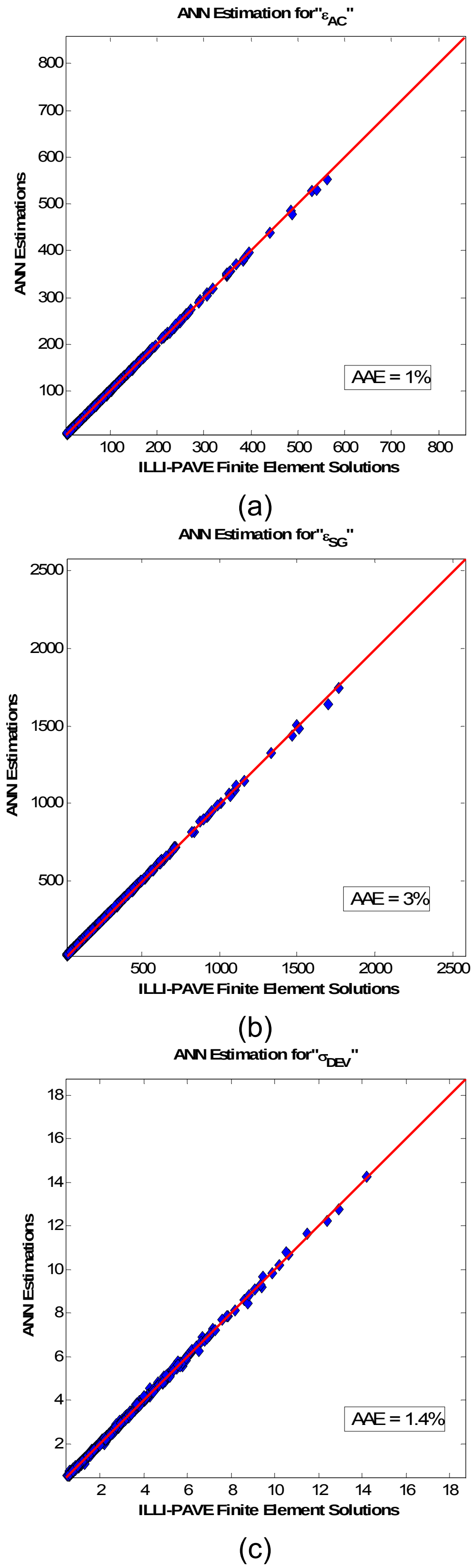


Figure 3-17. Comparisons of ANN structural model predictions with ILLI-PAVE results for full-depth asphalt pavement critical pavement responses (strains in microstrain and stress in psi).

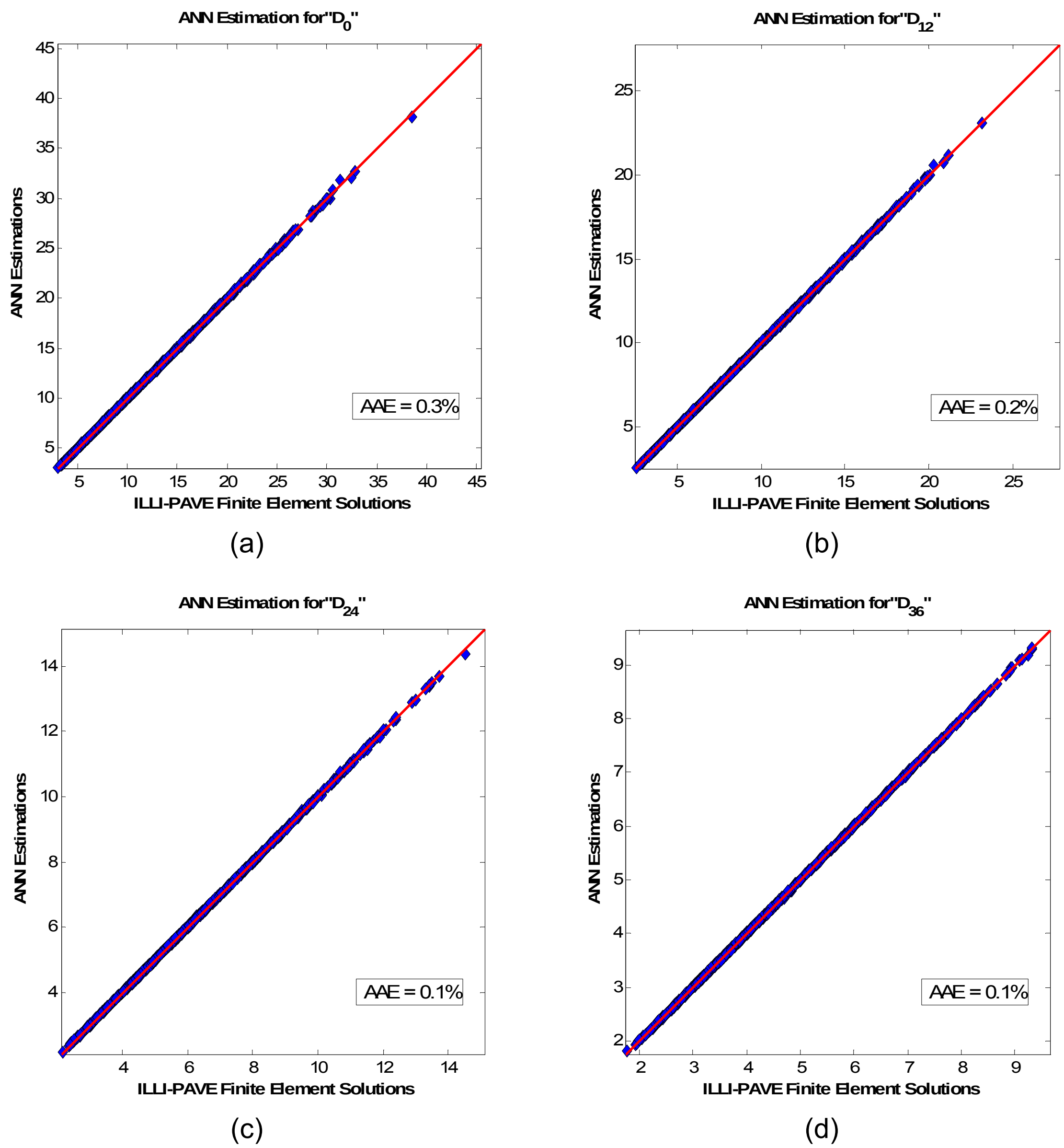
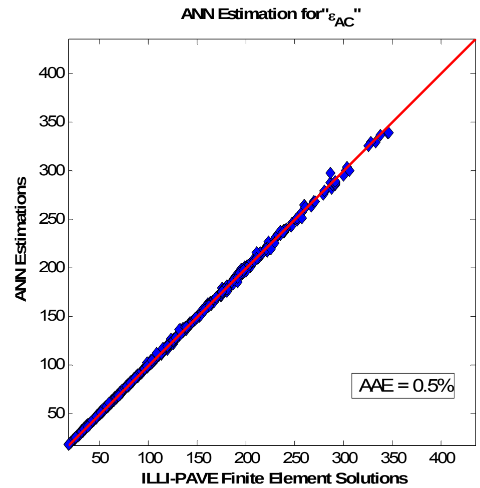


Figure 3-18. Comparisons of ANN structural model predictions with ILLI-PAVE results for conventional flexible pavement surface deflections (in mils).



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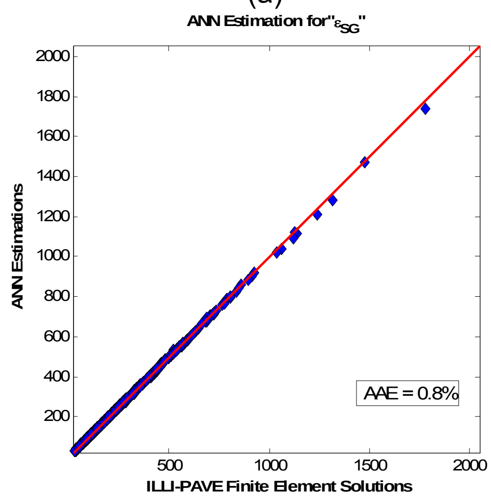

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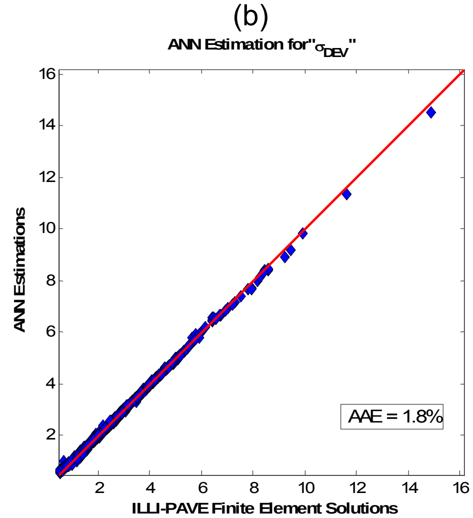

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Figure 3-19. Comparisons of ANN structural model predictions with ILLI-PAVE results for conventional flexible pavement critical pavement responses (strains in microstrain and stress in psi).

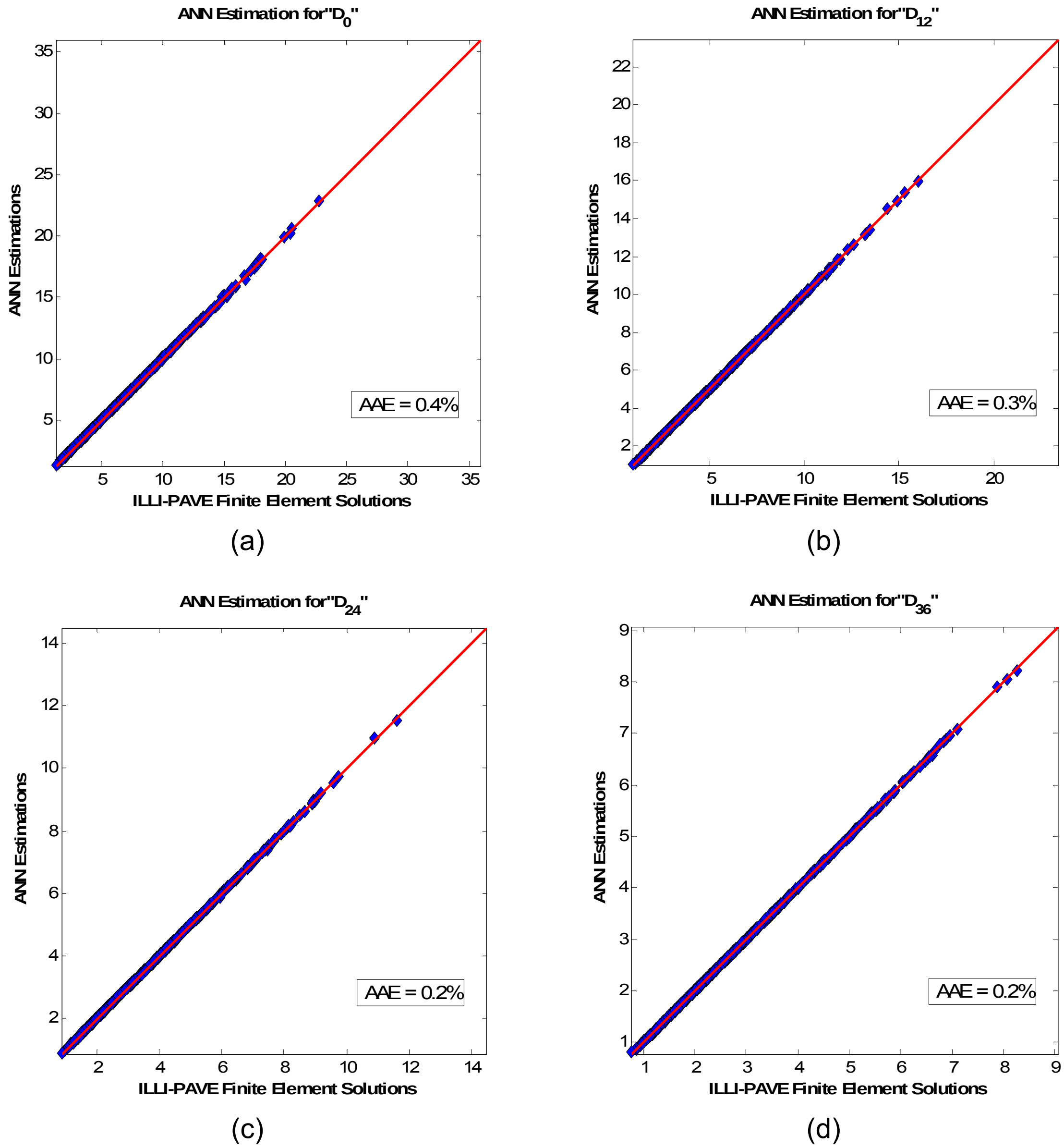
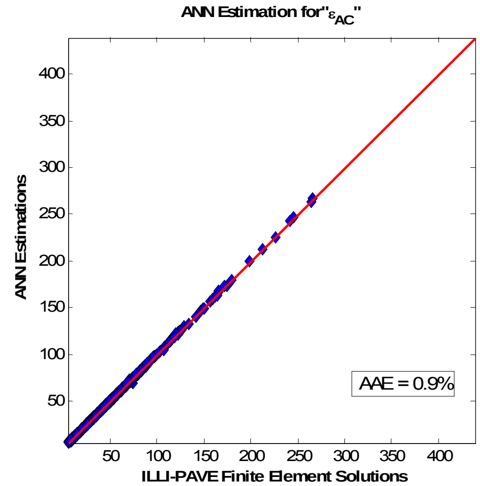
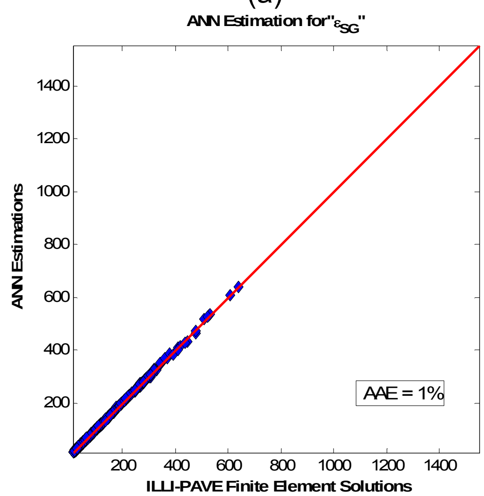


Figure 3-20. Comparisons of ANN structural model predictions with ILLI-PAVE results for surface deflections (in mils) of full-depth asphalt pavements built on lime stabilized soils.



(a)



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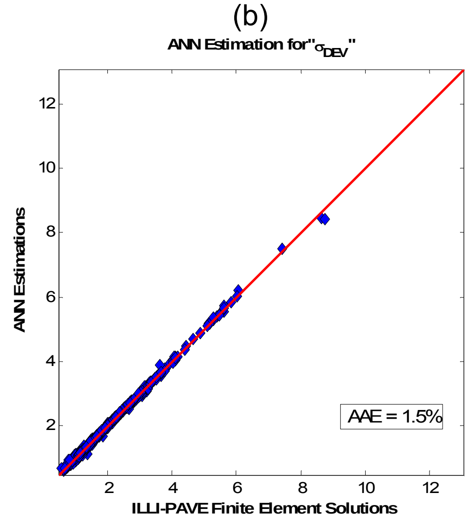

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Figure 3-21. Comparisons of ANN structural model predictions with ILLI-PAVE critical pavement responses of full-depth asphalt pavements built on lime stabilized soils (strains in microstrain and stress in psi).

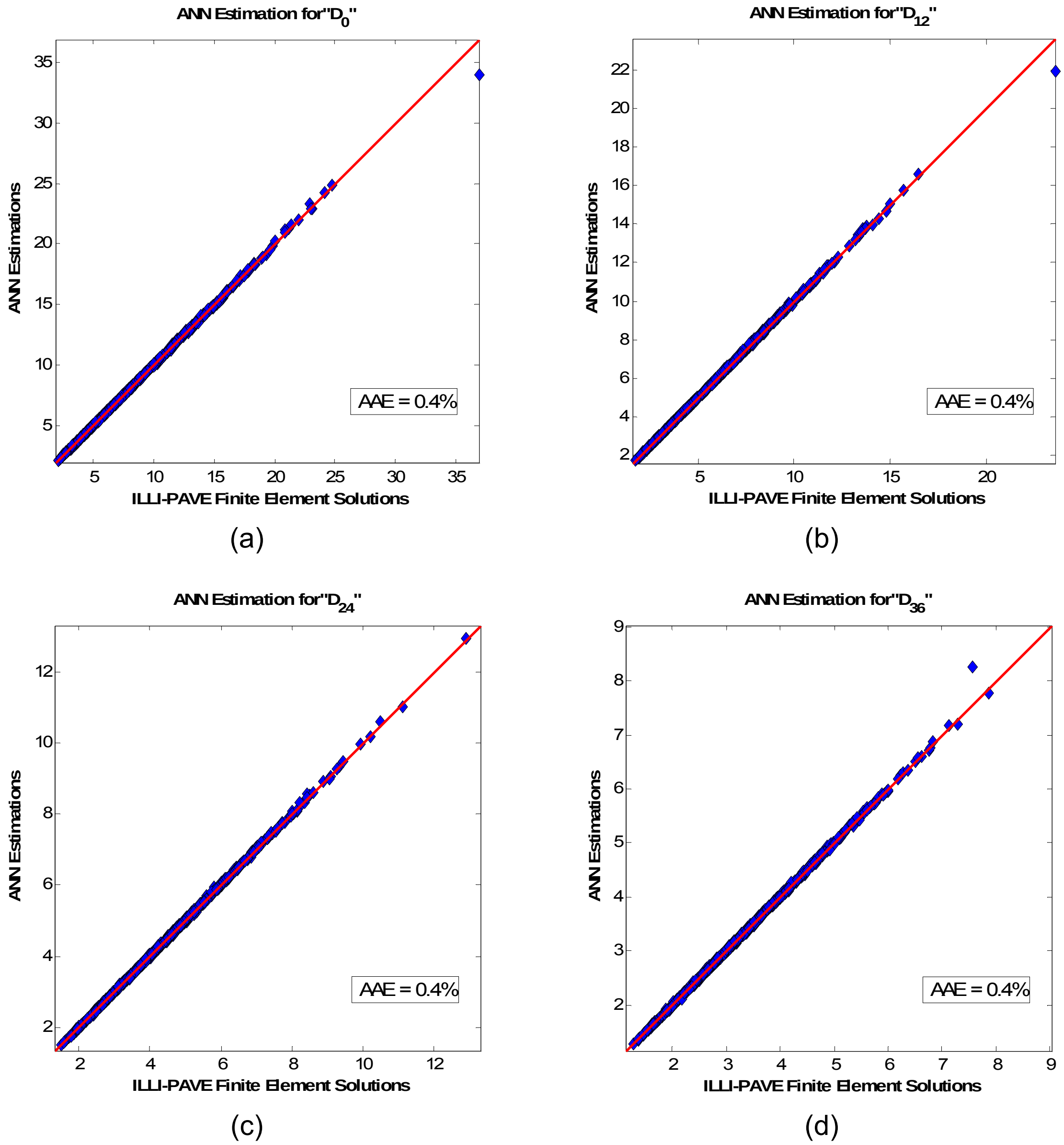
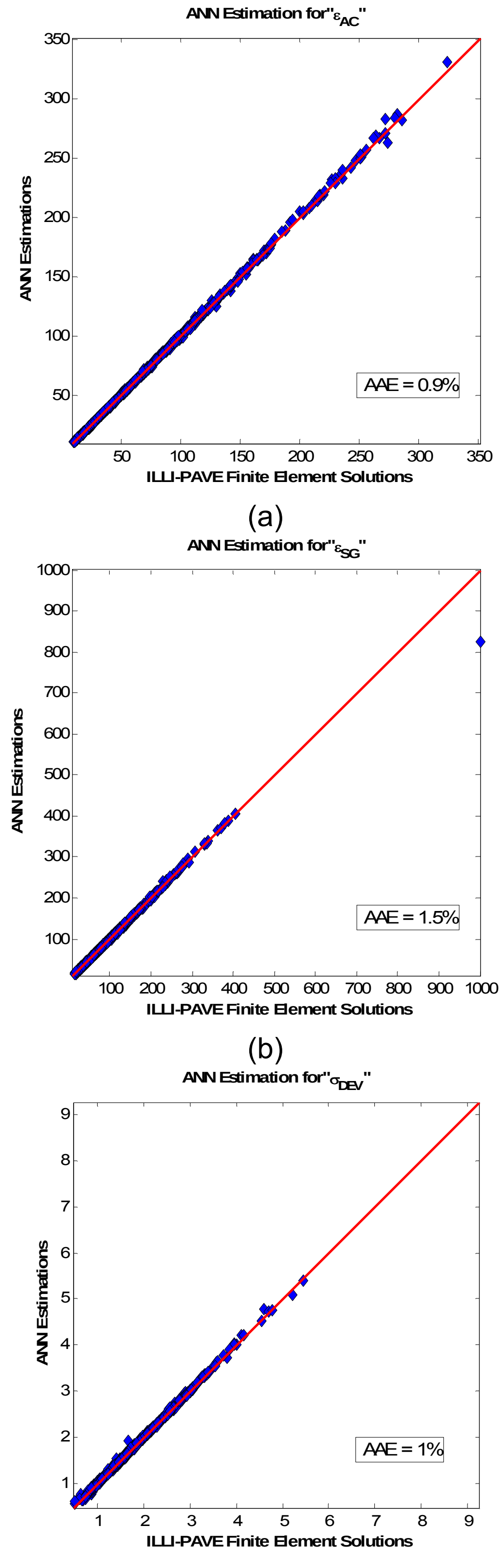


Figure 3-22. Comparisons of ANN structural model predictions with ILLI-PAVE results for surface deflections (in mils) of conventional flexible pavements built on lime stabilized soils.



(c)

Figure 3-23. Comparisons of ANN structural model predictions with ILLI-PAVE critical pavement responses of conventional flexible pavements built on lime stabilized soils (strains in microstrain and stress in psi).

3.4.2. Backcalculation Models

ANNs are very powerful and versatile computational tools for organizing and correlating information for certain types of problems in which the complexity and/or intensiveness of data resources are predominant. As such, ANNs have been used as a new class of computationally intelligent modeling systems for solving many geotechnical and transportation soils engineering problems including the pavement layer backcalculation application (Meier 1995). Yet, pavement structural analysis tools used to train ANN models were mainly linear elastic and did not account for the realistic stress sensitivity of geomaterials. Finite element programs with the nonlinear, stress dependent geomaterial characterization need to be used to generate solution databases for developing ANN-based structural models. Such uses of ANN models were intended in this section to rapidly and more accurately backcalculate field or in-service pavement layer properties as well as to predict critical stress, strain and deformation responses of these pavements in real time from the measured FWD deflection data.

The ILLI-PAVE database that was explained in the previous section was used here for training of ANN models in an inverse way. Various backcalculation models were developed for the rapid estimation of pavement layer properties. Two hidden layers were used in all ANN models to have adequate nonlinear functional mapping for computing the pavement responses and moduli of all flexible pavement layers (Ceylan et al. 2005). The specific ANN models trained and their input and output variables are listed in Tables 3.10 through 3.13. All ANN models had 60 neurons in the hidden layers and were trained for 10,000 epochs. The ANN models were then tested for their prediction abilities using 1,100 independent testing datasets for CFP and 1,000 testing datasets for FDP, FDP-LSS, and CFP-LSS pavements. The learning rates and the coefficients of momentum were adjusted and optimized to improve the ANN learning process when needed (Haykin 1999).

FDP-BW1 and CFP-BW1 models predict the layer moduli values from FWD deflections, as indicated in Tables 3.10 and 3.11, for both CFP and FDP pavements. CFP-BW2 model was trained to predict K_{GB} for CFPs with the CFP-BW1 results also used as inputs in addition to the FWD deflections. FDP-BW2 and CFP-BW3 models were developed to predict critical pavement responses directly from FWD deflections and layer thicknesses. In doing so, they can also calculate pavement responses without the need for a structural analysis model, such as the ILLI-PAVE FE program.

Similarly, FDP-LSS-BW1 model uses the deflection values D_0, D_{12}, D_{24}, D_{36} obtained from an FWD test and the pavement thicknesses t_{AC} and t_{LSS} of the FDP-LSS to predict E_{AC} and E_{Ri} at the same time. FDP-LSS-BW2 model takes all inputs and outputs of BW1 and treats them as additional inputs to predict E_{LSS}. In other words, the use of BW2 requires successful implementation of BW1. After E_{AC} and E_{Ri} are estimated, they are then utilized as inputs for the BW2 model. Using FDP-LSS-BW3 model, critical pavement responses can be calculated (Table 3.12).

Finally, there are a total of four ANN models developed for the backcalculation of CFP-LSS pavement layer properties. In all four ANN models developed, the deflection values D_0, D_{12}, D_{24}, D_{36}, D_{48}, D_{60} and D_{72} obtained from FWD testing and the pavement thicknesses t_{AC}, t_{GB}, and t_{LSS} were used as inputs. CFP-LSS-BW1 model is used to backcalculate just the layer moduli E_{AC} and E_{Ri}. CFP-LSS-BW2 model predicts the critical pavement responses ε_{AC}, ε_{SG}, and σ_{DEV}. These are the first two ANN models to run for a given problem set. A sequential approach thereby employed computes next the remaining GB and LSS layer properties such that CFP-LSS-BW3 model uses the critical pavement responses obtained from the CFP-LSS-BW2 model to determine K_{GB}. Similarly, CFP-LSS-BW4 model requires the CFP-LSS-BW3 output K_{GB} to determine E_{LSS} accurately (Table 3.13). In practice, models 3 and 4 may produce less accurate results since the errors can be accumulative.

Table 3.10. Backcalculation ANN Models for Full-Depth Asphalt Pavements

Name	Inputs	Outputs
FDP-BW1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}	E_{AC}, E_{RI}
FDP-BW2	D_0, D_{12}, D_{24}, D_{36}, t_{AC}	ε_{AC}, ε_{SG},σ_{DEV}

Table 3.11. Backcalculation ANN Models for Conventional Flexible Pavements

Name	Inputs	Outputs
CFP-BW1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{GB}	E_{AC}, E_{RI}
CFP-BW2	D_0, D_{12},D_{24}, D_{36}, t_{AC}, t_{GB}, E_{AC}, E_{RI}	K_{GB}
CFP-BW3	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{GB}	ε_{AC}, $\varepsilon_{SG,}\sigma_{DEV}$

Table 3.12. Backcalculation ANN Models for Full-Depth Asphalt Pavements on Lime Stabilized Soils

Name	Inputs	Outputs
FDP-LSS-BW1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{LSS}	E_{AC}, E_{RI}
FDP-LSS-BW2	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{LSS},E_{AC}, E_{RI}	E_{LSS}
FDP-LSS-BW3	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{LSS}	ε_{AC}, $\varepsilon_{SG,}\sigma_{DEV}$

Table 3.13. Backcalculation ANN Models for Conventional Flexible Pavements on Lime Stabilized Soils

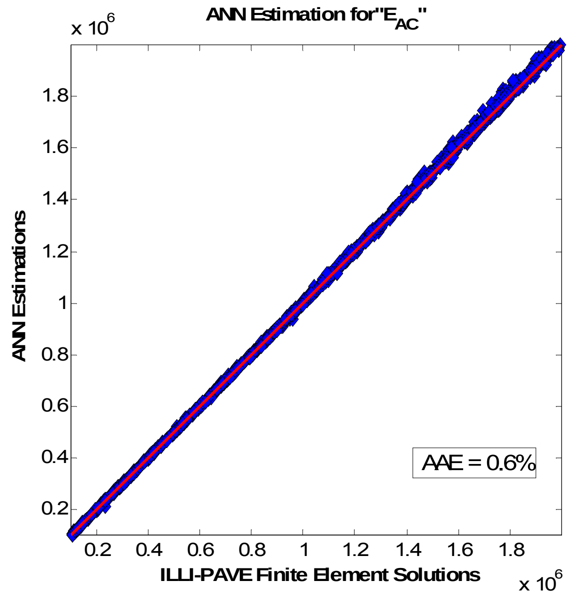
Name	Inputs	Outputs
CFP-LSS-BW1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{GB}, t_{LSS}	E_{AC}, E_{RI}
CFP-LSS-BW2	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{GB}, t_{LSS}	ε_{AC}, ε_{SG}, σ_{DEV}
CFP-LSS-BW3	D_0, D_{12}, D_{24}, D_{36}, D_{48}, D_{60}, D_{72}, t_{AC}, t_{GB}, t_{LSS}, ε_{AC}, ε_{SG}, σ_{DEV}	K_{GB}
CFP-LSS-BW4	D_0, D_{12}, D_{24}, D_{36}, D_{48}, D_{60}, D_{72}, t_{AC}, t_{GB}, t_{LSS}, E_{AC}, E_{RI}, K_{GB}	E_{LSS}

3.4.2.1 Performances of the Developed ANN Models

The performances of the developed ANN models are illustrated in Figures 3-24 to 3-31 along with the computed AAE values. Figures 3-24 and 3-26 indicate that the asphalt concrete moduli of both FDP and CFP pavements were predicted with the lowest AAEs when compared to those of the base and subgrade nonlinear modulus model parameters. Usually, K_{BASE} was found to be the most difficult to predict, although in this case, the combined use of CFP-BW1 and CFP-BW2 models worked quite effectively for improving predictions. All critical pavements responses were also predicted quite successfully with AAE values less than 6.1% corresponding to very low and almost negligible values of actual strain and stress magnitudes (see Figures 3-25 and 3-27).

ANN model performances for backcalculated FDP-LSS pavement layer moduli are given in Figures 3-28(a) to (c). The average absolute errors (AAEs) given indicate that FDP-LSS-BW1 model could predict ILLI-PAVE solutions within very low 1.3% and 2.1% AAEs for E_{AC} and E_{Ri}, respectively, while the accuracy of FDP-LSS-BW2 model for the prediction of E_{LSS} remains within a very low AAE of 2.3%. All critical pavement responses were also predicted quite successfully (see Figure 3-29). The maximum AAE value of 3.2% was obtained for the subgrade deviator stress and the strain predictions had much lower AAE values.

Comparisons of CFP-LSS pavement layer moduli predictions with ILLI-PAVE results are given in Figures 3-30 (a) through (d) with the corresponding AAE values. CFP-LSS-BW1 model could predict E_{AC} and E_{RI} values in the ILLI-PAVE database within AAE values of 2.1% and 4.7%, respectively. In addition, AAE values from CFP-LSS-BW2 model are 0.9%, 6.1%, and 4.6% for ε_{AC}, ε_{SG}, and σ_{DEV}, respectively (see Figure 3-31). The predictions of K_{GB} and E_{LSS} layer properties, however, produced slightly higher AAE values of 7.7% and 6.6%, respectively. It was observed that the layer properties that could not be predicted with high accuracy by CFP-LSS-BW3 and 4 usually belonged to the pavement sections with extremely thick LSS and GB layers. In practice, however, these pavement geometries are very rare in Illinois and often not constructed with proper quality control and quality assurance practices.



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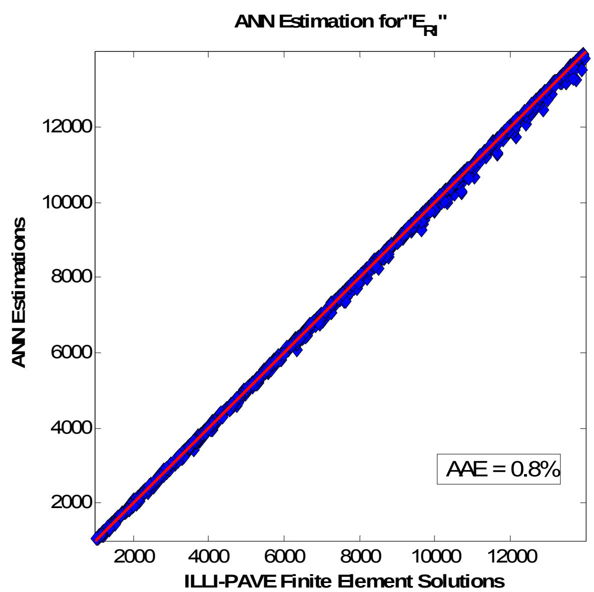
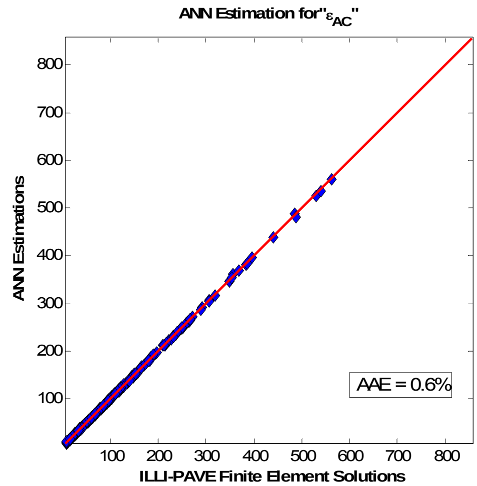


(b)

Figure 3-24. Performances of ANN backcalculation models for predicting layer moduli (in psi) of full-depth asphalt pavements.



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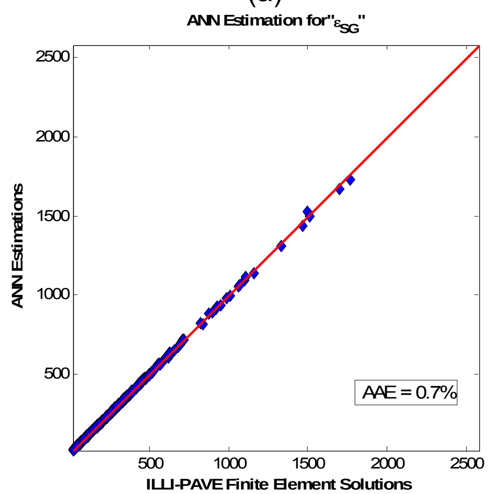

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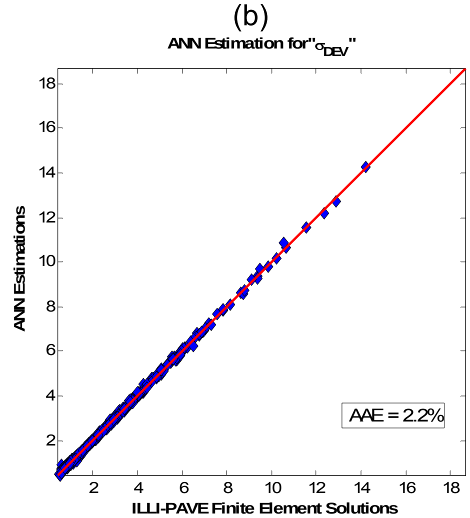

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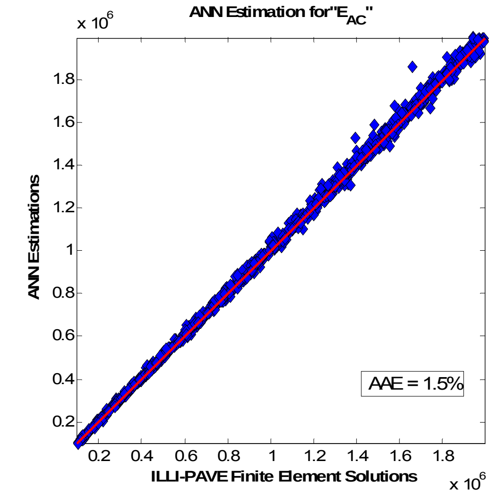
Figure 3-25. Performances of ANN backcalculation models for predicting critical pavement responses of full-depth asphalt pavements (strains in microstrain and stress in psi).



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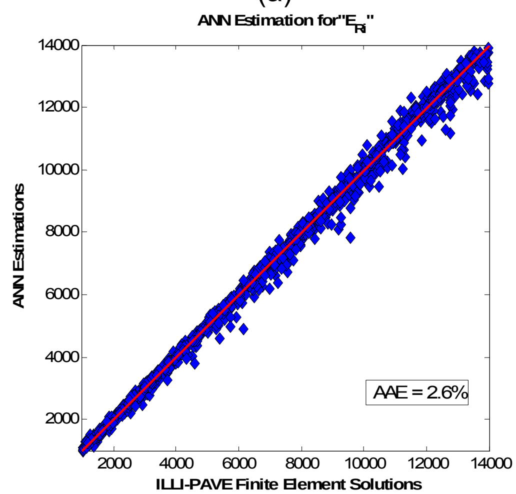

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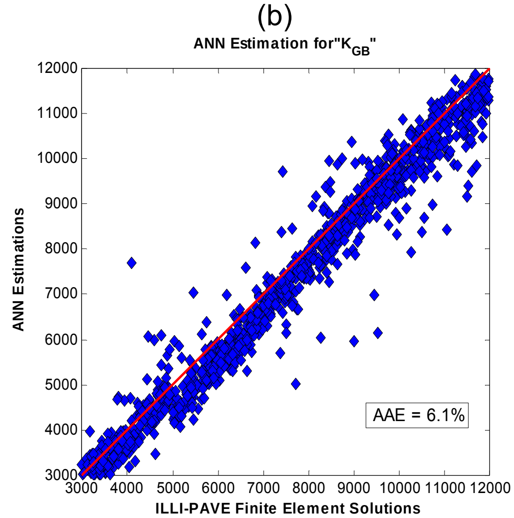
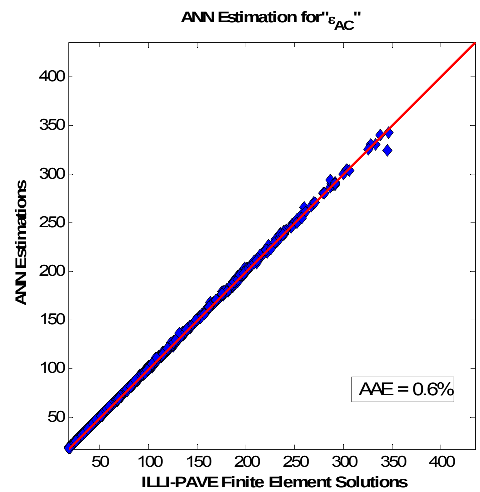
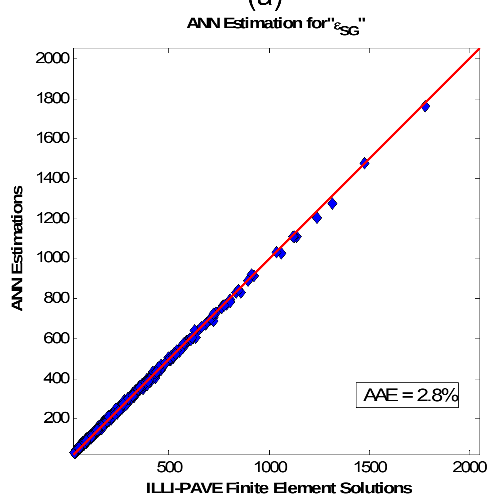


(c)

Figure 3-26. Performances of ANN backcalculation models for predicting layer moduli (in psi) of conventional flexible pavements.



(a)



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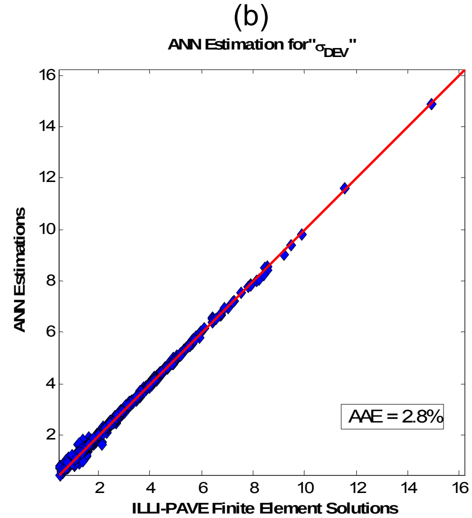

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Figure 3-27. Performances of ANN backcalculation models for predicting critical pavement responses of conventional flexible pavements (strains in microstrain and stress in psi).

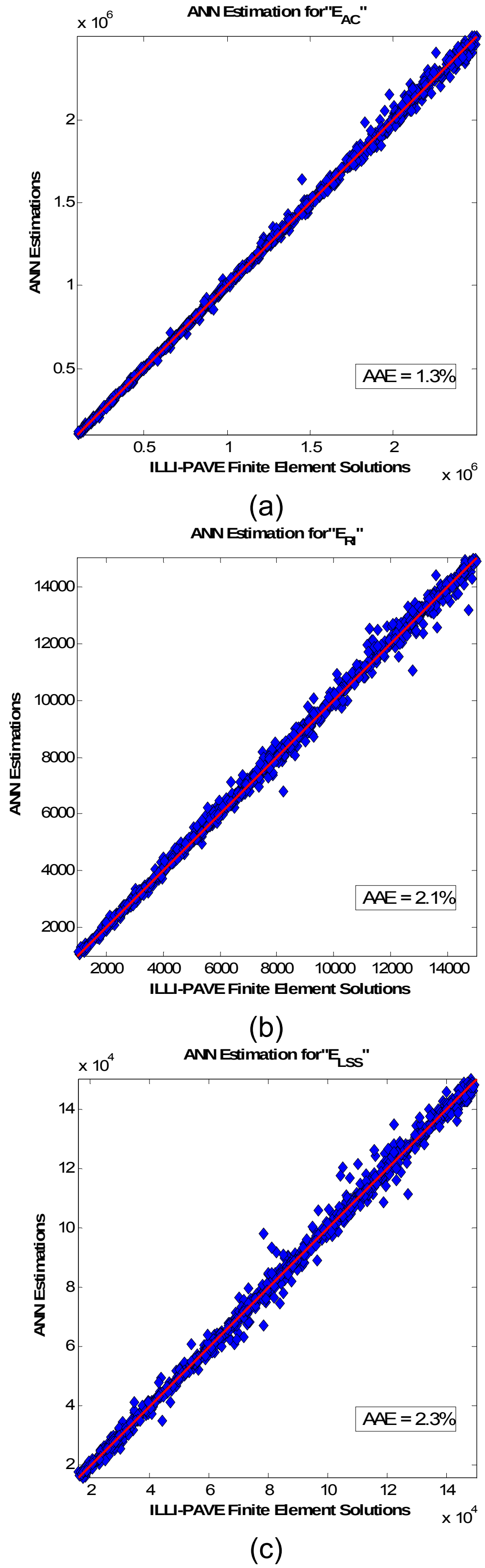
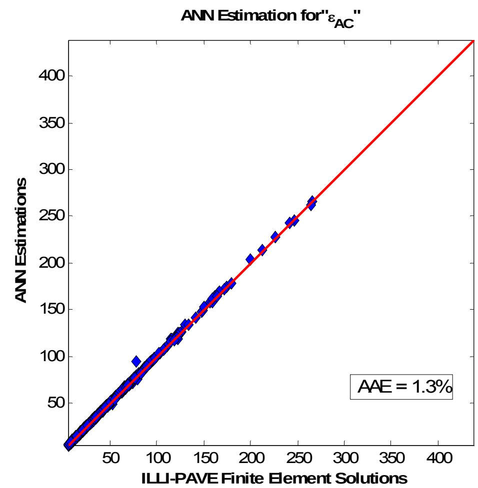
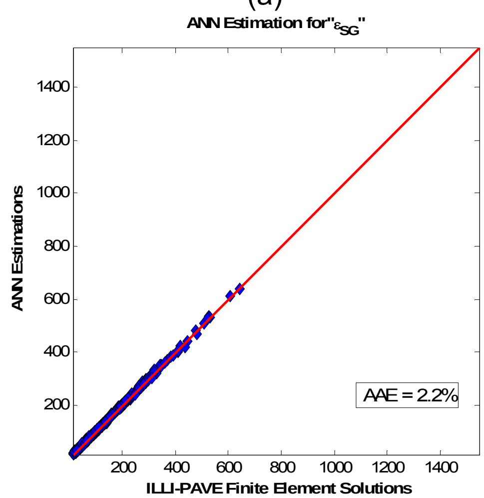


Figure 3-28. Performances of ANN backcalculation models for predicting layer moduli (in psi) of full-depth asphalt pavements built on lime stabilized soils.



(a)



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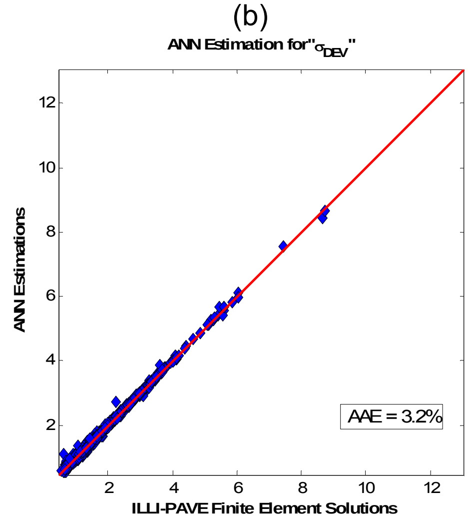


(c)

Figure 3-29. Performances of ANN backcalculation models for predicting critical pavement responses of full-depth asphalt pavements built on lime stabilized soils (strains in microstrain and stress in psi).

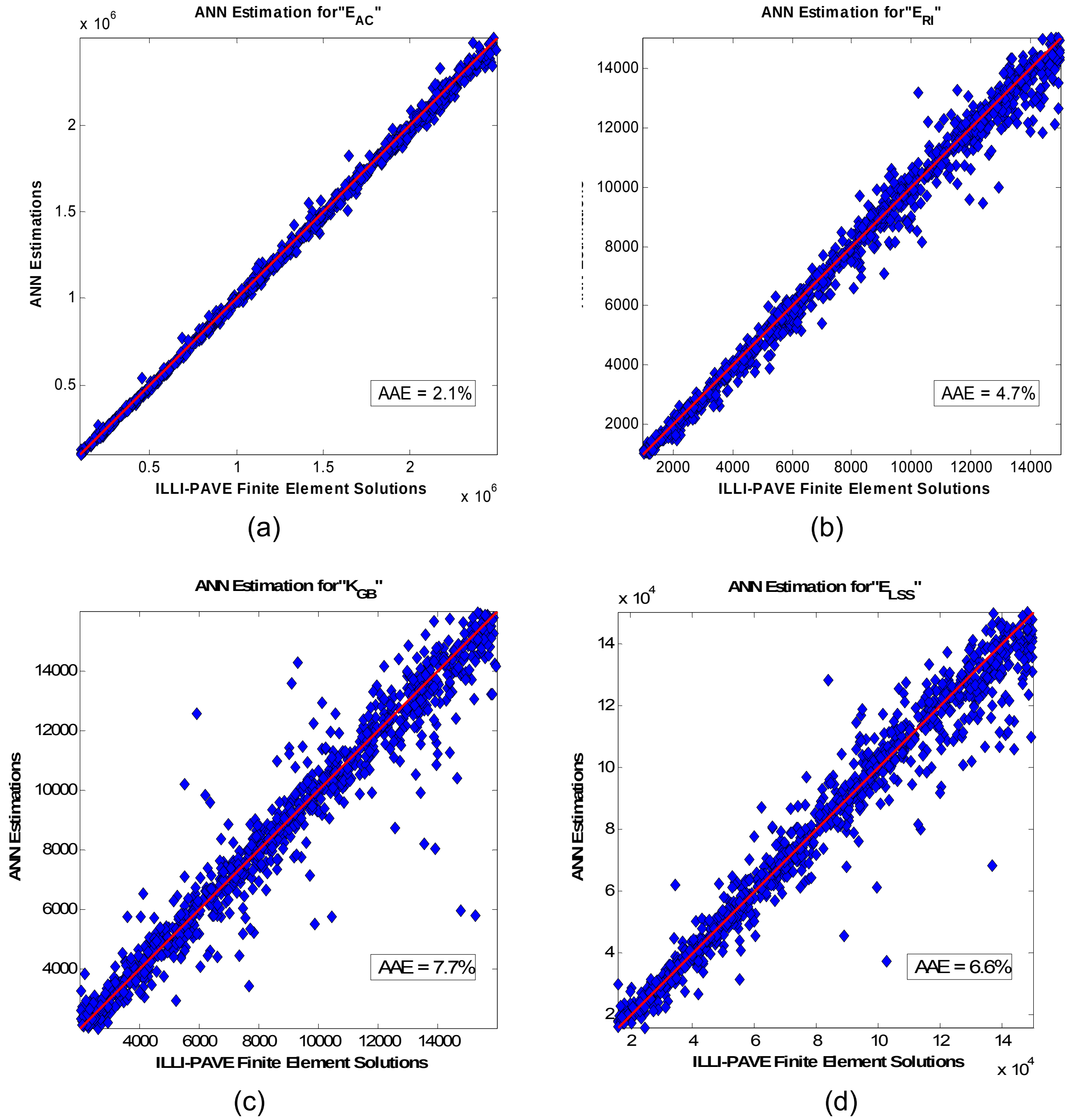
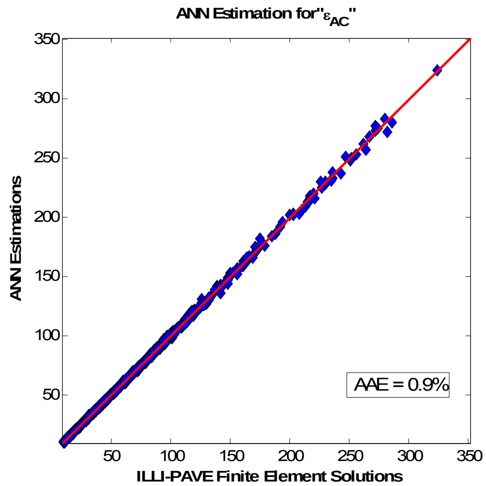
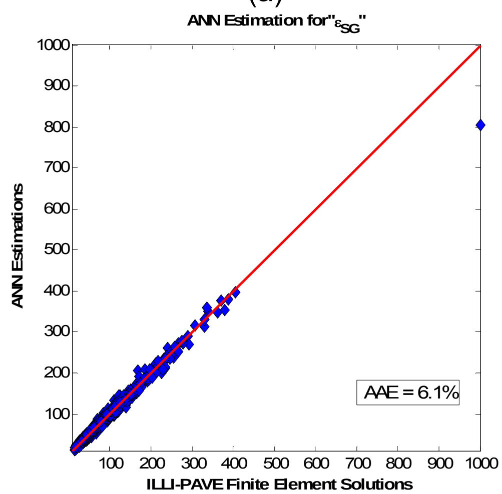


Figure 3-30. Performances of ANN backcalculation models for predicting layer moduli (in psi) of conventional flexible pavements built on lime stabilized soils.



(a)



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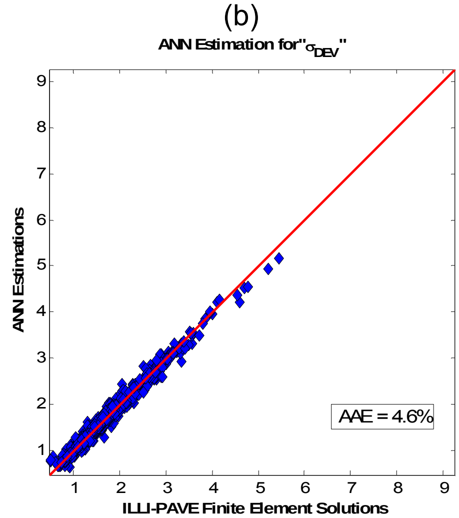


(c)

Figure 3-31. Performances of ANN backcalculation models for predicting critical pavement responses of conventional flexible pavements built on lime stabilized soils (strains in microstrain and stress in psi).

3.5 FIELD VALIDATION

The performances of the developed ANN models were deemed to be adequately verified using the testing datasets by the good comparisons of ANN model predictions with the ILLI-PAVE results. However, it is always necessary to validate ANN model performances using actual field data especially when the training database has been created synthetically such as in this case using the ILLI-PAVE FE analyses. For this purpose, field data were collected from three highway condition assessment and rehabilitation projects provided by the Illinois Department of Transportation (IDOT) Bureau of Materials and Physical Research and used for the performance validations of the developed ANN models. The field data included both the FWD results as well as the information and test results obtained from cored pavement sections collected from the FWD locations. Note that most of the full-depth asphalt pavement sections in Illinois are built on lime stabilized soils although a very few sections also exist that are built on unmodified subgrade.

In addition, two sets of backcalculation algorithms, given below in Equations 3-4 to 3-7, for E_{AC} and E_{Ri} were chosen from the previous studies and/or current practice and used to further verify ANN model predictions for comparisons. Equations 3-4 to 3-7, referred to hereafter as Hill's algorithms (Hill and Thompson 1988), were separately developed with and without the consideration of existing LSS layers in FDPs. Whereas, equations 3-8 and 3-9, referred to hereafter as Thompson's algorithms, were developed only for FDPs without taking into account LSS layers (Thompson 1989). Note that Thompson's algorithms provide the set of equations currently in use by IDOT for FDP layer modulus backcalculation. All of these equations were developed based on ILLI-PAVE solutions and the statistical regression analyses of the field collected data, FWD test results with standard 9-kip loading, with a minimum correlation coefficient R^2 of 0.98 reported in the literature. In these equations, no temperature correction was included in backcalculation to account for different field pavement temperatures based on seasonal and daily temperature fluctuations.

<u>Hill's Equations for Lime Stabilized Sections:</u>

$$\log(E_{AC}) = 2.824 - 4.083\log(D_0 - D_{12}) + 3.478\log(D_0 - D_{24}) - 0.375\log(D_0 - D_{36}) - 0.382\frac{(D_{12} - D_{36})}{(D_{12} - D_{36})} \qquad (3\text{-}4)$$

$$E_{Ri} = 46.71 + 23.74\frac{\log(D_{24})}{\log(D_{36})} - 89.72(\frac{D_{24}}{D_{36}}) + 335.69\log(\frac{D_{24}}{D_{36}}) - 13.17\log(D_{24} - D_{36}) + 5.20\frac{(D_{12} - D_{36})}{(D_{12} - D_{24})} \qquad (3\text{-}5)$$

<u>Hill's Equations for No-Lime (unmodified subgrade) Sections:</u>

$$\log(E_{AC}) = 3.516 - 5.045\log(D_0 - D_{24}) - 0.479\log\frac{(D_0 - D_{36})}{(D_{12} - D_{24})} + 4.082\log(D_{12} - D_{36}) + 1.237\frac{(D_0 - D_{24})}{(D_{12} - D_{36})} \qquad (3\text{-}6)$$

$$E_{Ri} = -136.1 + 106.4\frac{\log(D_{24})}{\log(D_{36})} - 3.33(\frac{D_{12}}{D_{36}}) + 87.78\log(\frac{D_{12}}{D_{24}}) - 58.75\log(D_{12} - D_{36}) - 4.27\log(D_{12} - D_{36}) \qquad (3\text{-}7)$$

<u>Thompson's Equations :</u>

$$\log(E_{AC}) = 1.846 - 4.902\log(D_0 - D_{12}) + 5.189\log(D_0 - D_{24}) - 1.282\log(D_{12} - D_{36}) \qquad (3\text{-}8)$$

$$E_{RI} = 24.7 - 5.41D_{36} + 0.31D_{36}^{2} \qquad (3\text{-}9)$$

where E_{AC} and E_{Ri} are in ksi and D_0, D_{12}, D_{24}, and D_{36} are in mils.

3.5.1 High Cross Road (FA 808)

High Cross Road is located in the southeast corner of the City of Urbana in Champaign County, Illinois. The pavement cross section from original design consists of 11 in. of hot mix asphalt (HMA) surface on top of 11 in. of LSS. The FWD tests were performed along highway sections 201 and 201B. The total length of highway mileage for the FWD data collection was approximately 2.28 miles. The pavement temperature was approximately 54°F when the FWD tests were performed. Figures 3-32 (a)-(d) show the backcalculation performances of the ANN models developed for FDP-LSS pavements for High Cross Road in comparison to the predictions from Hill's and Thompson's backcalculation algorithms (Equations 3-4, 3-5, 3-8 and 3-9) for E_{AC} and E_{Ri}.

3.5.2 Roseville Bypass

Roseville Bypass is a connector road to accommodate US-67 traffic. The design pavement cross section consists of 14 in. of HMA and a 12-in. thick LSS layer. The FWD tests were performed on part C of the Roseville Bypass, which is a connector road approximately 300 ft. in length. The pavement temperature was reported as 97°F along the road during the FWD tests. Figures 3-33 (a)-(d) show the performances of the ANN models developed for FDP-LSS pavements in comparison to the predictions from Hill's and Thompson's backcalculation algorithms (Equations 3-4, 3-5, 3-8 and 3-9) for E_{AC} and E_{Ri}.

3.5.3 Staley Road

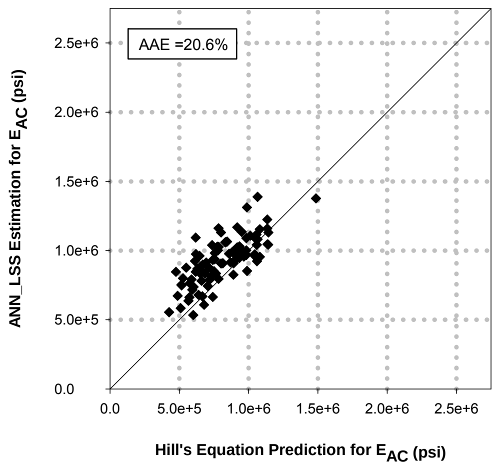
Staley Road runs in north-south direction and is located on the west end of the City of Champaign in Champaign County, Illinois. The design pavement cross section consists of 12 in. of HMA constructed on LSS with a thickness of 12 in. The FWD tests were performed along a 2-mile stretch of highway. The pavement temperature was reported as 75°F along the road on the day of FWD tests. Figures 3-34 (a)-(d) show the performances of the ANN models developed for FDP-LSS pavements for Staley road in comparison to the predictions from Hill's and Thompson's backcalculation algorithms (Equations 3-4, 3-5, 3-8 and 3-9) for E_{AC} and E_{Ri}.

3.5.4 US 50 (FAP 327, old FA 409)

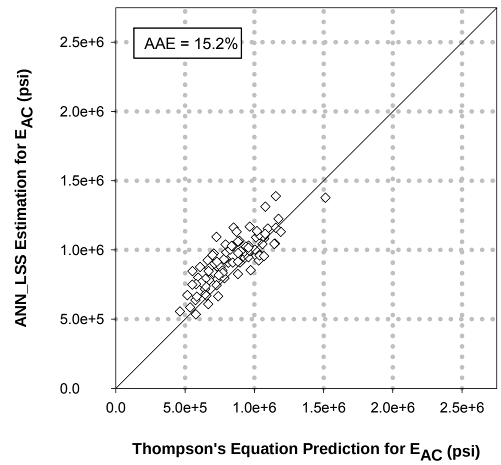
US 50 is located in both St. Clair County and Clinton County in Illinois. The design pavement section is 9.5 in. of HMA built on unmodified subgrade. The FWD data belonging to test section K in St. Clair County and section M2 in Clinton County were analyzed. The pavement temperature was reported to be 95°F for both sections on the day of FWD tests. Figures 3-35 (a)-(d) show the performances of the ANN models developed for FDP pavements in comparison to the predictions from Hill's and Thompson's backcalculation algorithms (Equations 3-6, 3-7, 3-8 and 3-9) for E_{AC} and E_{Ri}.

3.5.5 US 20 (FAP 301, old FA 401)

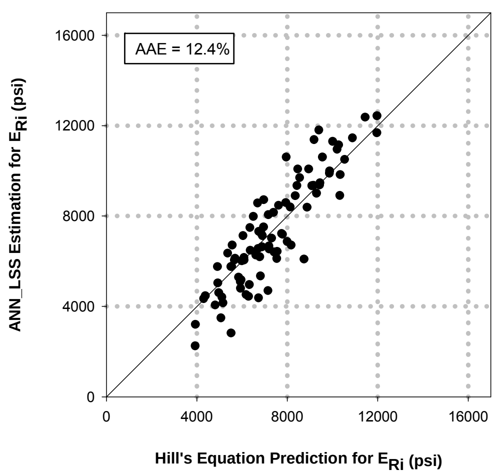
US 20 is located in Stephenson County in Illinois. The design pavement section is 13 in. of HMA built on unmodified subgrade. The FWD tests were performed on both sections A and B, which are approximately 200 ft. in length. The pavement temperature was reported to be 99°F for both sections on the day of FWD tests. Figures 3-36 (a)-(d) show the performances of the ANN models developed for FDP pavements in comparison to the predictions from Hill's and Thompson's backcalculation algorithms (Equations 3-6, 3-7, 3-8 and 3-9) for E_{AC} and E_{Ri}.



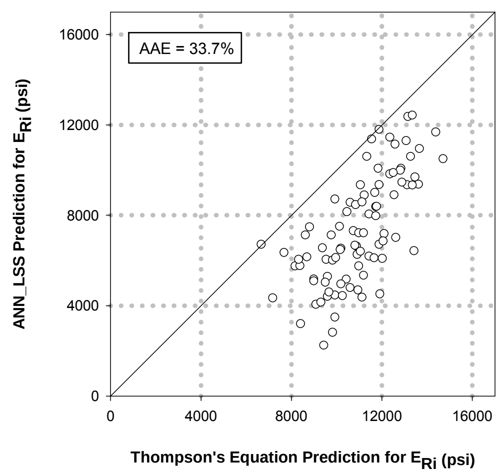
(a) Hill's Algorithm for E_{AC}



(b) Thompson's Algorithm for E_{AC}

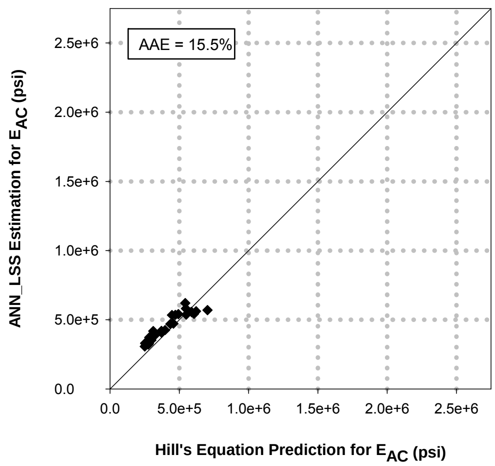


(c) Hill's Algorithm for E_{Ri}

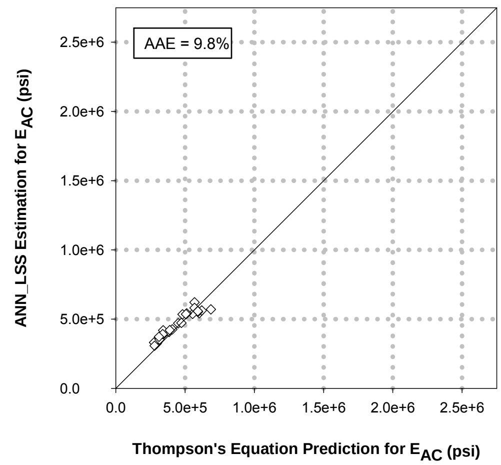


(d) Thompson's Algorithm for E_{Ri}

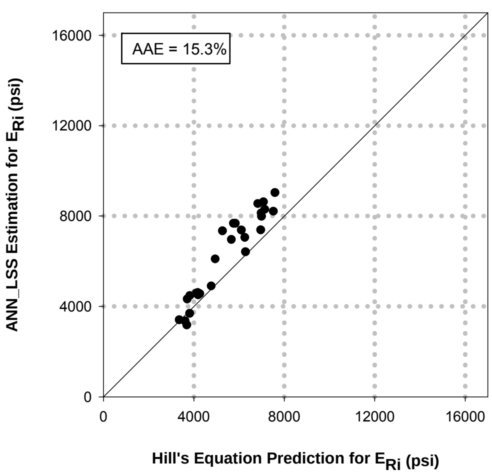
Figure 3-32. Performances of FDP-LSS ANN models for High Cross Road.



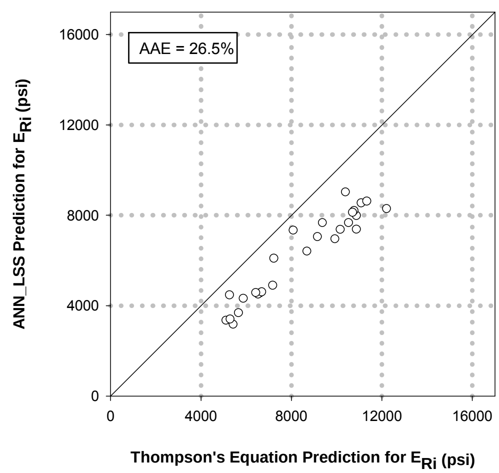
(a) Hill's Algorithm for E_{AC}



(b) Thompson's Algorithm for E_{AC}

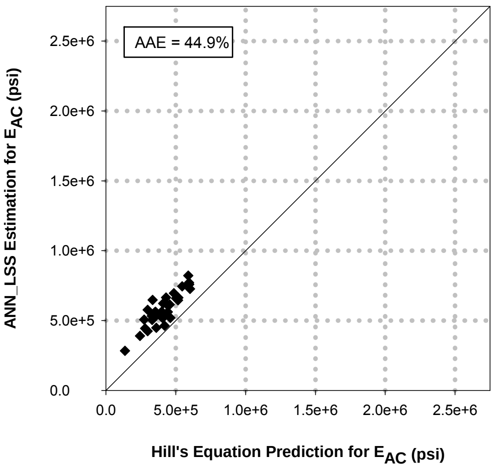


(c) Hill's Algorithm for E_{Ri}

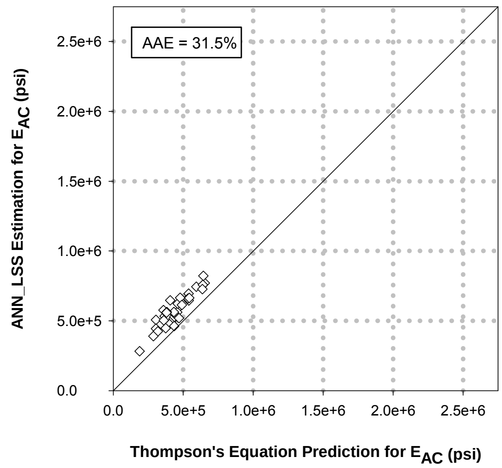


(d) Thompson's Algorithm for E_{Ri}

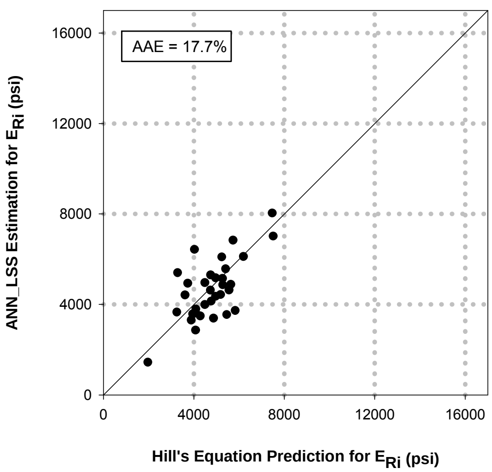
Figure 3-33. Performances of FDP-LSS ANN models for Roseville Bypass.



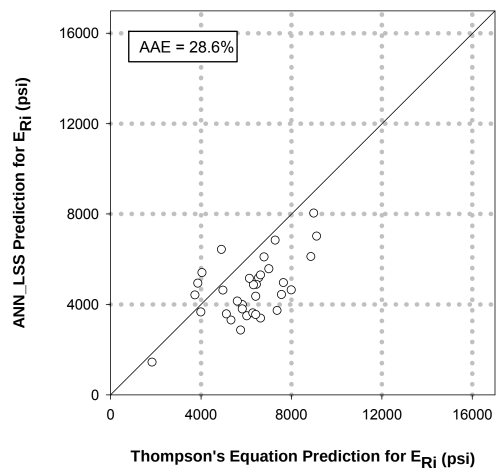
(a) Hill's Algorithm for E_{AC}



(b) Thompson's Algorithm for E_{AC}

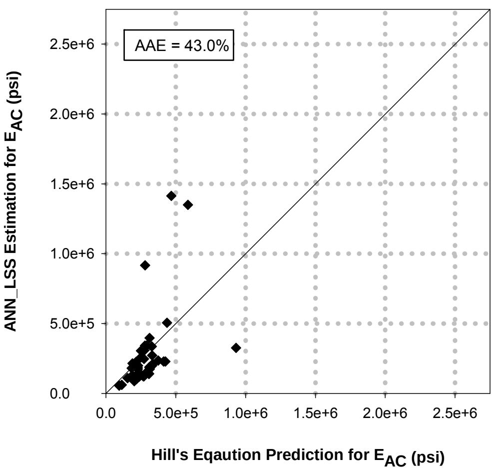


(c) Hill's Algorithm for E_{Ri}

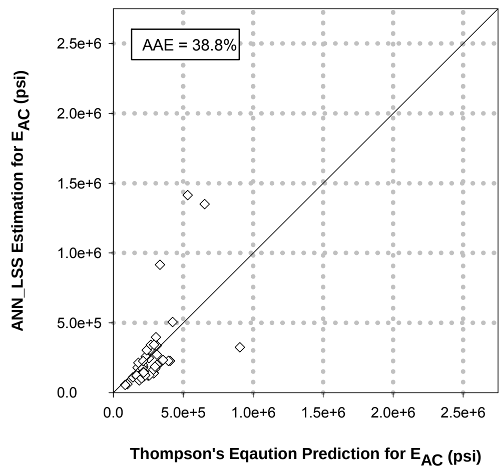


(d) Thompson's Algorithm for E_{Ri}

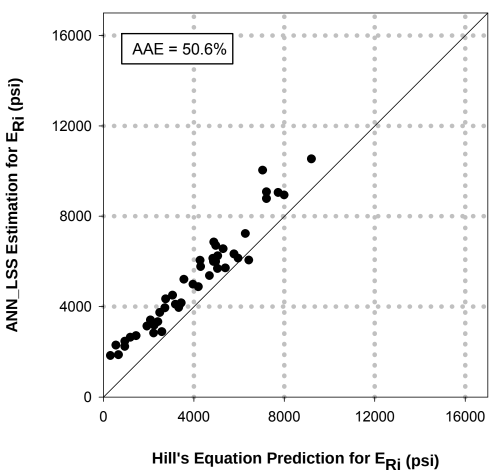
Figure 3-34. Performances of FDP-LSS ANN models for Staley Road.



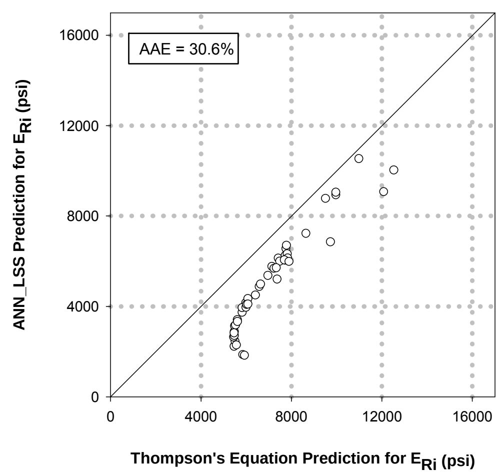
(a) Hill's Algorithm for E_{AC}



(b) Thompson's Algorithm for E_{AC}

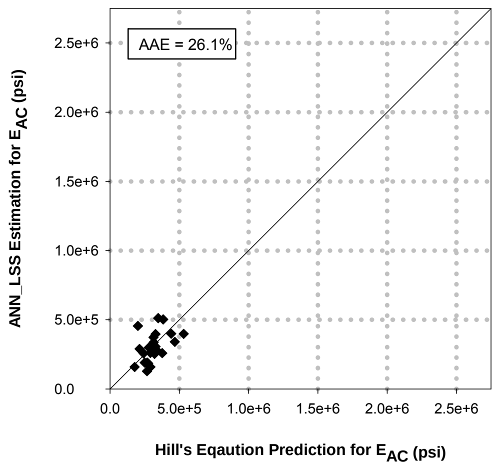


(c) Hill's Algorithm for E_{Ri}

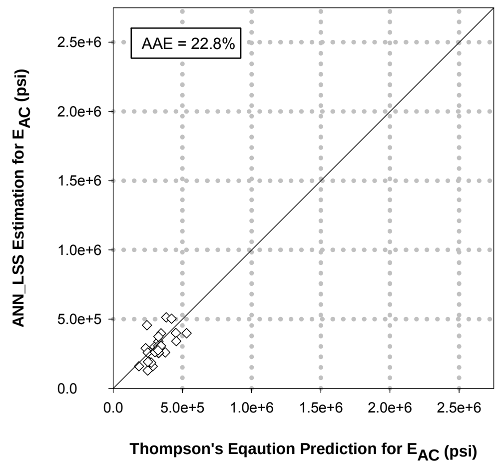


(d) Thompson's Algorithm for E_{Ri}

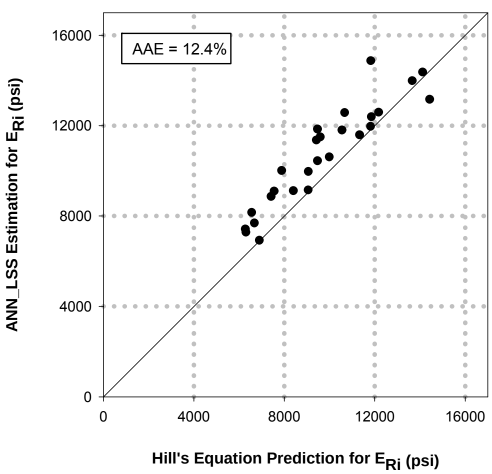
Figure 3-35. Performances of FDP ANN models for US 50.



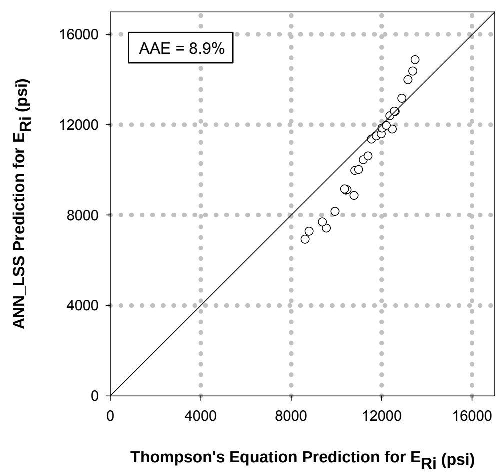
(a) Hill's Algorithm for E_{AC}



(b) Thompson's Algorithm for E_{AC}



(c) Hill's Algorithm for E_{Ri}



(d) Thompson's Algorithm for E_{Ri}

Figure 3-36. Performances of FDP ANN models for US 20.

For all the field validation performances shown in Figures 3-32 to 3-34, ANN-LSS models captured the AC moduli of FDP-LSS pavements practically the same with both Hill's and Thompson's algorithms. This is possibly due to the fact the effect of LSS is mostly pronounced in the estimation of E_{Ri} and the AC layer moduli are not affected significantly by the presence of the LSS layer. However, Hill's equations, developed for the FDP-LSS pavements, produced overall better and more comparable estimates with the ANN models. This was clearly indicated as Hill's E_{Ri} predictions were better centered on the 45-degree equality line with the ANN predictions whereas E_{Ri} values predicted by Thompson's algorithms were in general much lower in magnitude than the ANN results. A possible explanation of this is linked to the nonlinear stress dependent modulus behavior of the fine-grained subgrade soils as shown in Figure 3-4. As the wheel load deviator stresses become lower under the LSS layer, typically higher moduli are predicted for the untreated subgrade layer by the ANN models in comparison to those estimated by Thompson's algorithm.

The field validation performances for FDPs are shown in Figures 3-35 to 3-36. Similar to FDP-LSS, ANN models developed for FDPs captured the AC moduli practically the same with both Hill's and Thompson's algorithms. Hill's equations, developed for the estimation of E_{Ri} of FDPs, produced overall better and more comparable estimates with the ANN models. This was clearly indicated as Hill's E_{Ri} predictions were better centered on the 45-degree equality line with the ANN estimates whereas E_{Ri} values predicted by Thompson's algorithms were in general much lower in magnitude than the ANN results.

Some of the variability in the presented data can also be attributed to variations in the actual constructed thicknesses of both HMA and LSS layers. Not all the field pavement thicknesses were verified with collected pavement cores. To overcome this difficulty in the future, field thicknesses should be determined at the FWD locations. Alternatively, sensitivities of the backcalculation models to imprecise layer thicknesses should be better assessed and possibly made more robust.

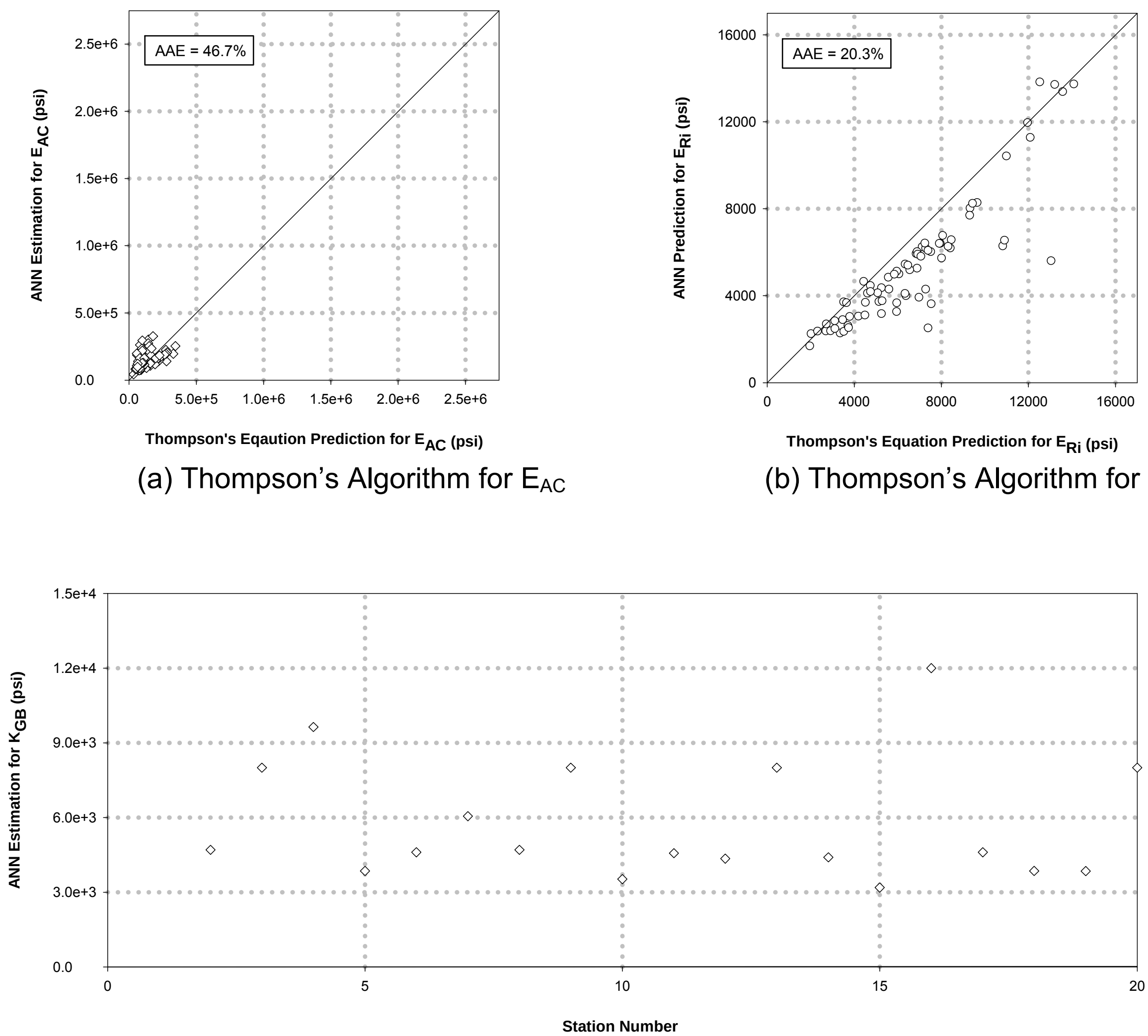
3.5.6 Sand Pit Road (Henry County)

Sand Pit Road was one of the very few CFP sections that were analyzed among all other FWD data. The design pavement section is 3.5 in. of HMA and 16 in. of granular base built on unmodified subgrade. Pavement temperatures show large variations throughout the road, changing from 63°F to 88°F on the day of FWD tests. Figures 3-37 (a)-(b) show the performances of the developed ANN models for backcalculating E_{AC} and E_{Ri} layer properties of CFPs in Henry County, Illinois in comparison to the Thompson's algorithm predictions given in Equations 3-10 and 3-11 (Thompson 1989) . In addition, K_{GB} estimation along the road is given in Figure 3-37 (c).

<u>Thompson's Equations :</u>

$$\log(E_{AC}) = 1.31 + 8.01\frac{D_{12}}{D_0} - 13.0\frac{D_{12}}{D_{24}} + 6.58\frac{D_{36}}{D_{24}} - 0.081D_0 + 0.096D_{12} \qquad (3\text{-}10)$$

$$E_{RI} = 24.7 - 5.08D_{36} + 0.28D_{36}^{\ 2} \qquad (3\text{-}11)$$



(a) Thompson’s Algorithm for E_{AC} (b) Thompson’s Algorithm for E_{Ri}

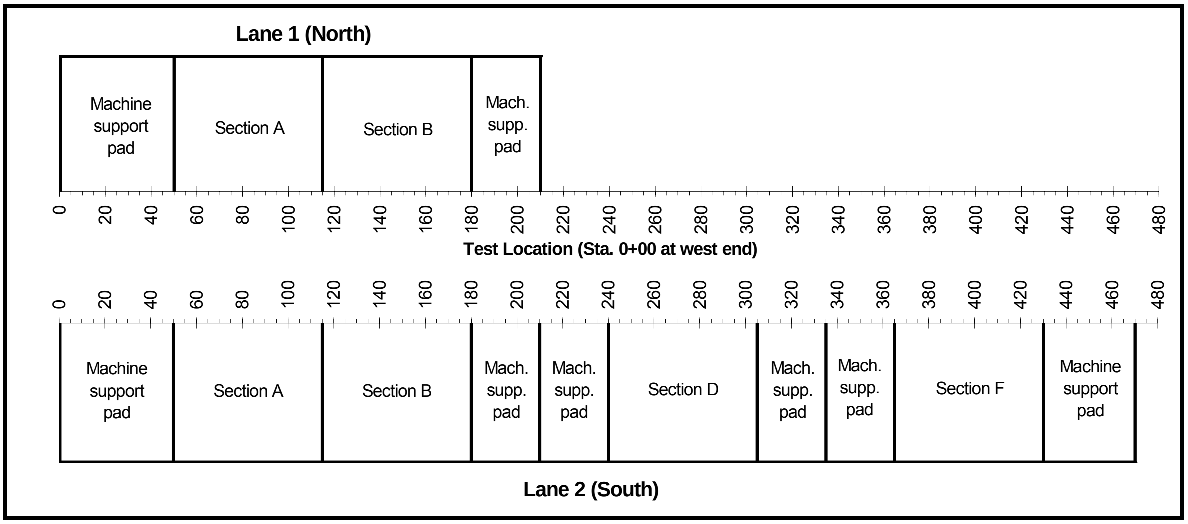
(c) K_{GB} Estimation

Figure 3-37. Performances CFP ANN models for Sand Pit Road.

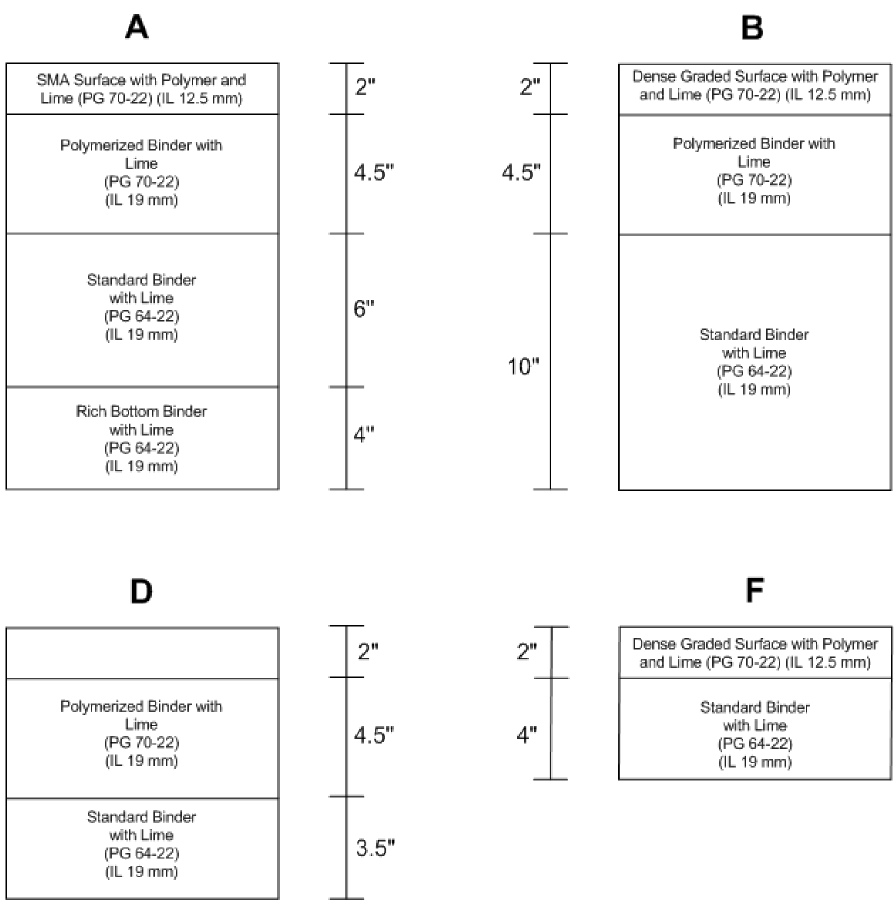
3.5.7 ATREL Test Sections

In an attempt to further verify ANN structural models developed for flexible pavements in this study, FWD tests were performed at the University of Illinois Advanced Transportation Research and Engineering Laboratory (ATREL) pavement test sections. The plan views and cross section details of the test sections are given in Figures 3-38(a) and (b). FWD tests were conducted on test sections A, D, and F shown in Figure 3-38. The pavement temperature was reported to be between 80 to 85°F on the day of FWD tests. Since most of the rather high deformations obtained from FWD testing on section F are beyond the limits of ANN structural models, section F FWD results could not be utilized. Figure 3-39 (a)-(d) show the performances of the developed FDP-LSS ANN models for

ATREL sections A and D pavements in comparison to the predictions from Hill's and Thompson's backcalculation algorithms (Equations 3-5, 3-6, 3-8 and 3-9) for E_{AC} and E_{Ri}.

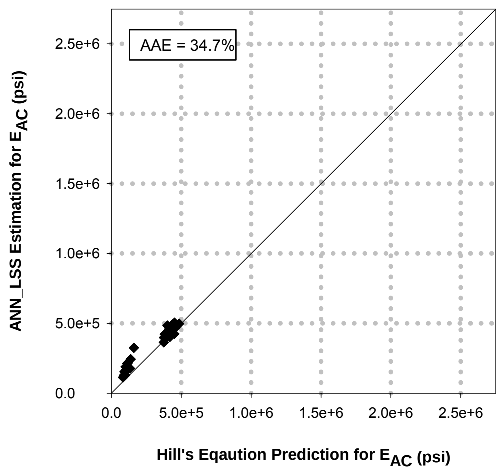


(a) Plan views of ATREL pavement test sections

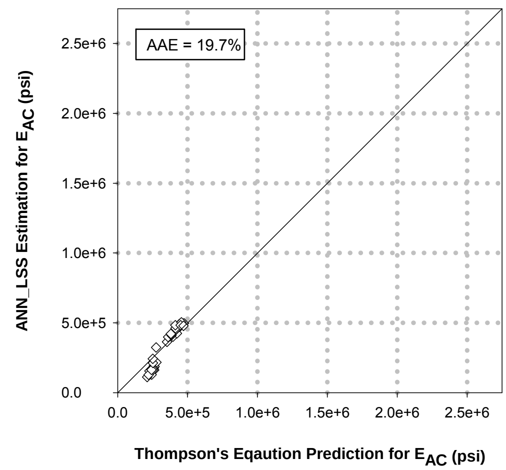


(b) Design thicknesses of ATREL pavement test sections

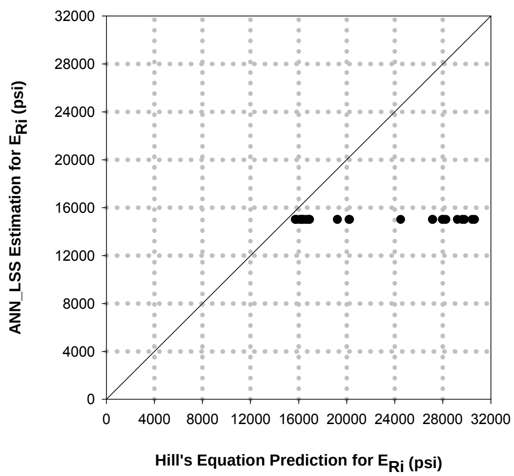
Figure 3-38. ATREL test sections.



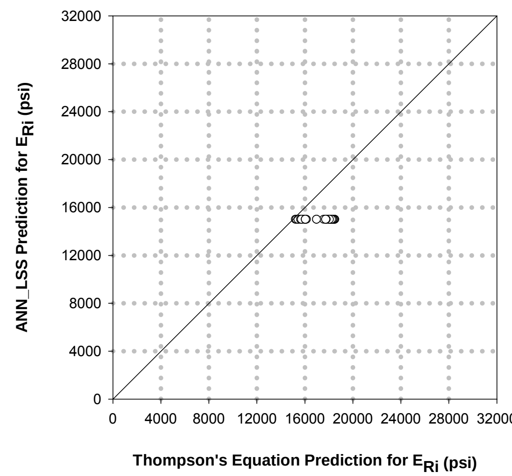
(a) Hill's Algorithm for E_{AC}



(b) Thompson's Algorithm for E_{AC}



(c) Hill's Algorithm for E_{Ri}



(d) Thompson's Algorithm for E_{Ri}

Figure 3-39. Performances of FDP-LSS ANN models for ATREL.

For all the field validation performances shown in Figures 3-39 (a)-(d), the FDP-LSS ANN models predicted the AC moduli in good agreement with both Hill's and Thompson's algorithms. However, both Hill's equations and Thompson's equations produce much higher estimations for E_{Ri}, since the normalized D_{36} values were very small numbers. Indeed, these values were beyond the ANN training ranges, i.e., ANNs hit the upper bound (limit for ANN training) for the prediction of E_{Ri}. A further attempt to calculate lime stabilized soil layer modulus was therefore not tried.

CHAPTER 4: SOFT COMPUTING BASED SYSTEM ANALYZER: SOFTSYS

4.1 INTRODUCTION

A typical pavement structure, as shown in Figure 4-1, can be identified using four different properties listed below (Selezneva et al. 2002). These properties need to be determined in order to have an overall pavement rehabilitation strategy:

- Layer descriptions (e.g., surface, overlay, base, and subgrade);
- Material type descriptions of pavement layers;
- Layer thicknesses;
- Layer thickness variability.

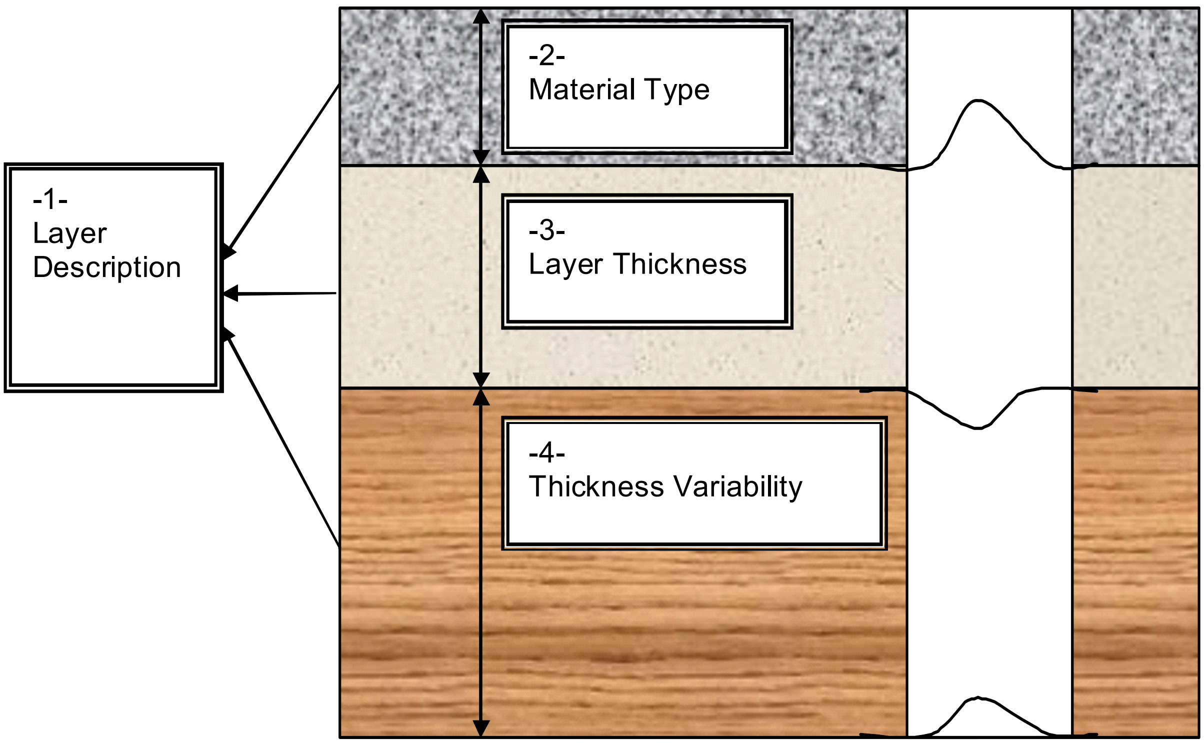


Figure 4-1. Typical pavement system parameters to be determined.

In the previous chapter of this report it was proven that properly trained artificial neural network (ANN) models as computational intelligence or soft computing tools are capable of backcalculating flexible pavement layer moduli and predicting pavement critical responses with average errors much smaller than those obtained with the statistically formulated algorithms currently in use by Illinois DOT. The nonlinear ILLI-PAVE FE program, an extensively tested and validated flexible pavement mechanistic analysis program for over the past three decades, has been used as the primary analysis tool for the solution of full depth and conventional flexible pavement responses under the standard 9-kip FWD loading. ANN models then trained with the results of the ILLI-PAVE solutions have been found to be viable alternatives to backcalculate the pavement layer moduli and predict the critical pavement responses based on the FWD deflection data. This demonstrated a significant level of improvement in the nondestructive FWD test data interpretations. The developed ANN models were validated to provide more accurate and rapid (real-time) analyses of the collected FWD deflection data, however, these ANN models require that FWD results be provided along with pavement layer thicknesses.

In this chapter, an innovative methodology, called SOFTSYS, is introduced for interpreting the results of a FWD test. It is a computational method to describe the properties of pavement layers. Among those, the layer thickness plays the crucial role in determining the remaining life since it is a major factor contributing to structural adequacy of the pavement. The outstanding contribution of SOFTSYS is that it is able to estimate the pavement layer thicknesses reliably in addition to their stiffness properties. Using only FWD test results (i.e. deflections) as inputs, SOFTSYS calculates all the necessary properties for pavement evaluation. To do this, SOFTSYS uses a combination of nontraditional computing tools, such as Artificial Neural Networks (ANNs) and Genetic Algorithms (GAs). Using quick and robust algorithms in SOFTSYS, real time evaluation of the pavements becomes feasible to also verify as-constructed pavement design parameters in the field.

4.2 OBJECTIVE

Knowing pavement layer thicknesses is critical to predicting pavement performance, establishing pavement load carrying capacity and developing pavement maintenance and rehabilitation strategies. Accurate determination of pavement layer thicknesses usually requires proper sampling from the pavement section (through the use of destructive testing). This is usually not preferred since it prevents functionality of a pavement and disrupts traffic. Moreover, thickness measurements obtained from only a few extracted cores may not always represent adequately the thickness profile. It is important to ensure that the thickness of materials being placed by the contractor is acceptably close to specifications (Sener et al. 1998).

The layer thickness information, a key structural design input, is mainly required for many types of analyses including backcalculation of pavement moduli, mechanistic analysis of pavement structures, and performance modeling. Due to poor workmanship and/or limitations of construction equipment used to build roads, construction quality of pavements may not be at a desired level. This might cause the thickness constructed on site to be considerably different than the designed thickness. Furthermore, in many cases, the lack of proper design documentation for existing roads makes it extremely difficult to rehabilitate certain pavements without the knowledge of pavement layer thicknesses. Insufficient knowledge of layer thicknesses during pavement response testing is therefore often a major limitation in pavement condition assessment.

The current methods to determine the thickness usually require coring of pavement or using some advanced nondestructive testing equipment such as Ground Penetrating Radar (GPR). These techniques are rather expensive or may result in destruction of pavement layer profile. On the other hand, if FWD tests are conducted, for example, in 5 ft intervals of the road section, in which the abrupt change in the thickness is not expected, the thickness profile along the pavement section can be determined with reasonably good accuracy and in real time.

To address the current challenges, SOFTSYS is developed to perform the following task in real time as part of conducting FWD tests:

- Determination of pavement thickness
- Estimation of pavement moduli
- Identifying pavement parameters such as poison’s ratio

4.3 BASICS OF SOFTSYS

SOFTSYS interprets FWD test results and performs pavement structural analysis based on the Finite Element Method (FEM). FEM provides modeling of pavement structure due to applied wheel loading to compute pavement deflections. Unlike the linear elastic theory commonly used in pavement analysis, nonlinear unbound aggregate base, and subgrade soil characterization models are used in the FEM. This accounts for the typical hardening behavior of unbound aggregate bases and softening nature of fine-grained subgrade soils under increasing stress states. The results of the nonlinear finite element approach have been proven to be consistent with the deflections obtained from NDT of pavements. Since FEM internally captures the nonlinear material properties to simulate the real pavement behavior, SOFTSYS, therefore, has an inherent capability of incorporating the nonlinear properties of aggregate and soil layers underneath pavements.

The implementation of soft computing methods is the next stage in the algorithm. The convergence of SOFTSYS when used with only FEM is quite slow. Therefore, FEM is replaced by ANNs since they work much faster and can still perform similar higher order function approximations as FEM. In addition, when ANNs are properly trained, they can tolerate errors that FWD tests might involve. This has been a major limitation with the classical approaches developed for interpretation of the test results. SOFTSYS, in addition, reliably implements GAs to feed inputs into ANN models. GAs are search algorithms for the optimum or maximum of complex objective functions (Goldberg 1989; Goldberg 2002). They contribute to the speed and robustness of SOFTSYS by performing fitness based search.

In conclusion, SOFTSYS features high reliability and advanced technology for predicting repeatable results in a quick and robust fashion to enable practical engineering interpretations of FWD test data essentially needed for nondestructive evaluation of pavements.

4.3.1 SOFTSYS Methodology and Algorithm

SOFTSYS is a computational methodology based on novel artificial intelligence techniques to backcalculate thickness and stiffness properties of the pavement layers. It also evaluates a pavement's structural adequacy in real time. It is a hybrid algorithm that combines three different techniques namely, Genetic Algorithms, Artificial Neural Networks, and nonlinear Finite Element Method. Each component performs certain tasks in order to run SOFTSYS at a desirable reliability, accuracy, and speed. SOFTSYS is introduced for the solution of the pavement backcalculation problem consisting of estimating layer thicknesses and moduli. It is an algorithm that uses a combination of GAs and ANNs as to guarantee that the proposed methodology becomes robust, quick, and imprecision tolerant. The flowchart of SOFTSYS is provided in Figure 4-2.

ANNs, in SOFTSYS, are used as quick and precise pavement structural analysis tools for the prediction of pavement deflection profiles. Training of ANNs is accomplished based on the results of nonlinear finite element analysis of pavements. Any sophisticated finite element program solution can be implemented in SOFTSYS. For the sake of providing results, ILLI-PAVE FE software that provides an advanced pavement structural model for solving deflection profiles and responses was selected. It can analyze any flexible pavement geometry, i.e., full-depth and conventional flexible pavements, due to an applied static loading. First, broad range of input parameters of the pavement layers (layer moduli and thicknesses) are created in a database. Then, randomly selected combinations of the parameters are inputted into ILLI-PAVE. Analyses are conducted for the simulation of FWD tests. Multi-layered, feed-forward backpropagation type ANNs (Wythoff 1993) are trained to capture the nonlinear relationships between the aforementioned input parameters and output variables (deflections) of ILLI-PAVE. The developed ANN model is ultimately used for computing pavement surface deflections based on the known pavement layer moduli and thicknesses.

GAs are computational models based on natural evolution (Holland 1975). They are powerful optimization and search methods. GA methodology is highly robust and imprecision tolerant. A system is represented by binary strings (i.e., genotype), which encodes the real values of parameters of the system (i.e., phenotype). A population with initial random parameters is used. Population members get better and better to satisfy the fitness criteria through number of generations. This is performed using the operators inspired by the nature such as competition, fitness based selection, crossover, and mutation. The results are not necessarily exact instead are accurate to a certain degree of approximation (Ghaboussi 2001).

In SOFTSYS, GAs work for random search with the operators inspired by the natural evolution. The major components of GAs are; the genotype / phenotype presentation of parameters of the problem domain (i.e., pavement layer moduli and thicknesses), fitness evaluation (mathematical expression as a measure of the difference between the surface deflections obtained by the FWD test and the ones calculated from ANN model), selection scheme, crossover method, and mutation. A collection of input parameters within a reasonable range are created randomly to have the database of all possible combinations of pavement layer material properties including material moduli and thickness encountered in the pavement. These are then fed into the ANN model as testing data set to compute the corresponding deflection profiles. The testing of all data sets created by GAs is done within a second, which is quite insensitive to number of testing data. GAs, then, sort input data set based on the imposed fitness function calculated using the outputs of ANN results and the deflection profile obtained by FWD testing. Natural evolution operators; selection, crossover, and mutation are then applied to the so called parents and to their offspring to establish the most satisfactory data set for the surface profile obtained from FWD. Finally, an iterative algorithm called “fine tuner” implemented into SOFTSYS has been intended to improve the precision of the obtained results.

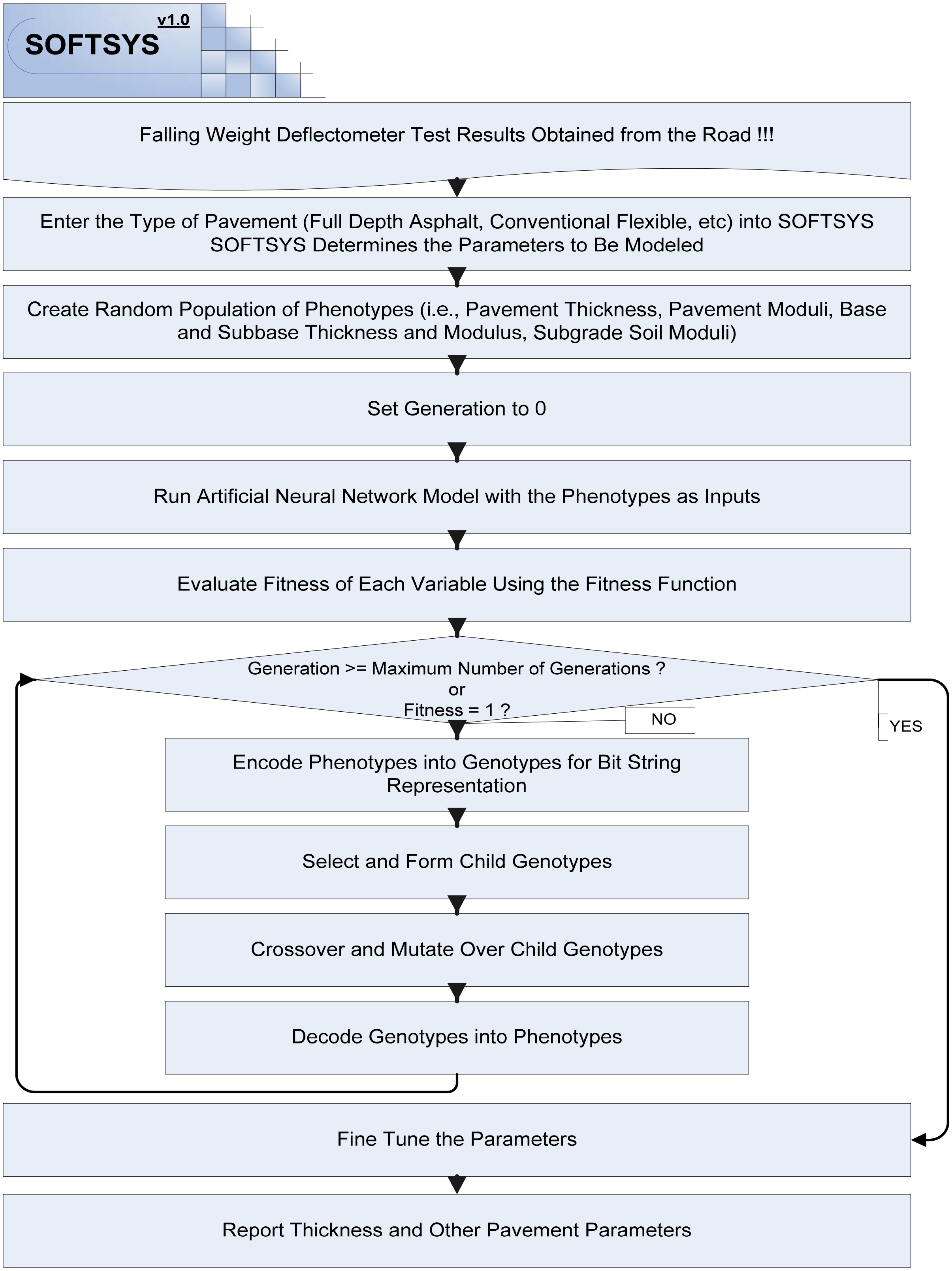


Figure 4-2. SOFTSYS algorithm.

4.3.2 SOFTSYS Description

In this section, SOFTSYS algorithm is explained step by step for practical purposes. Each step is described in detail to describe how robust solutions are obtained in SOFTSYS.

4.3.2.1 Inputting FWD Data

When Falling Weight Deflectometer (FWD) tests with 9-kip loading are conducted on any road section, the deflections obtained from the FWD testing on that typical road section are entered as an input file into the system.

Computer Implementation:

- For real time applications, input the deflection values (D0, D12, D24, D36, D48, D60, D72 - the last four values are optional);
- For offline analyses (after the whole test is carried on each station of the road), an input file is generated consisting of the deflection values for each station);
- In addition to FWD deflections, the conditions of the road (i.e., any comment of the technician, description of any observed crack, joint, etc.) and weather information (i.e., temperature) needs to be entered into the system.

4.3.2.2 Entering Pavement Type and Model

Based on the pavement type (Full-Depth Asphalt Pavement, Full Depth Asphalt Pavement on Lime Stabilized Soils, etc.) parameters to be modeled in SOFTSYS are entered.

Computer Implementation:

- Query for type of the pavement;
- Full-Depth Asphalt Pavement (FDP) or Full-Depth Asphalt Pavement on Lime Stabilized Soils (FDP-LSS) (there is going to be more categories of pavements as the ANN analyses show good progress);
- Based on the pavement category selected, the corresponding ANN structural model has to be introduced to the system. The ANN model parameters (so called phenotypes for genetic algorithms), given in Table 4.1, are extracted from the selected model and shown on the screen.

4.3.2.3 Population Creation

Random population of phenotypes, i.e., AC modulus & thickness (t_{AC}, E_{AC}), lime stabilized layer modulus & thickness (t_{LSS}, E_{LSS}), and subgrade soil modulus (E_{RI}) are created at this stage.

The user is queried for the ranges, i.e., maximum and minimum values, of phenotypes. The number of bits necessary to represent the phenotype is found using the maximum value of the phenotype. A uniform random number generator is then used to create the population of phenotypes.

Computer implementation:

- Enter the maximum number of generations for analysis;
- Enter the population size (recommended value is 60);
- Enter the maximum and minimum values of the phenotypes;
- Determine the number of bits to represent the phenotype and to encode it into genotype;
- Keep the number of bits the same for the rest of the calculations.

4.3.2.4 Iteration Initiation

Iterations are initiated by setting the iteration, i.e., Generation, to 0

Computer Implementation:

- Set the generation number to 0.

4.3.2.5 Running ANN Forward Analysis

The trained ANN model is run with the randomly created Phenotypes as inputs.

Computer Implementation:

- Normalize the phenotypes to the range specified by the already developed model (for example, normalize the inputs to [-1, 1] and outputs to [0.1, 0.9]);
- Run the ANN program with number of training data sets to 0 and that of testing data is the population size.

The results of ANN model runs are then obtained and the deflection values are unnormalized to ranges of the developed file and reported.

4.3.2.6 Fitness Evaluation of Population

The fitness of each member is calculated using the fitness function.

Computer Implementation:

- Depending on the number of FWD outputs (typically 4 - D0, D12, D24, and D36), the fitness of each member is calculated using the following formula given in Equation 4-1;
- Fitness vector is then formed for the whole population.

$$Fitness = \frac{1}{1 + \sum_{i=1}^{4} \frac{(\beta * (FWD_i - ANN_i))^{\alpha}}{FWD_i}} \qquad (4\text{-}1)$$

where α and β are 2 and 100, respectively.

4.3.2.7 Checking Termination Criterion

This stage is where termination of SOFTSYS algorithm is checked against several different criteria. If Generation is less than the maximum number of generations or the fitness is less than 1 (for practical purposes, it is specified less than 0.9999), then the algorithm needs to be run for at least one more generation.

Computer Implementation:

- If the generation number is greater than the maximum number of generations or the value of any of the members of the population in the fitness vector is equal to 1 (or specified by the user such as 0.95), then stop running SOFTSYS and report the member with the highest fitness, fitness value, and the generation number on the screen and to a file.
- Otherwise go to the next stage.

4.3.2.8 Encoding Variables

The variables are converted, i.e., encoded, from Phenotypes into Genotypes (bit String Representation) using bit, i.e. base 2, conversion.

4.3.2.9 Selection of Child Genotypes

Parents are combined to form Child Genotypes

Computer Implementation:

- Query the user for which selection algorithm to be used;
- Implement the corresponding algorithm;
- According the specified selection algorithm, such as the roulette wheel or tournament selection, select the new parents to create the offsprings;
- The parents are then paired in order, i.e., 1-2, 3-4, etc.

4.3.2.10 Crossover and Mutation of Variables

Do crossover and mutation over child genotypes.

The user is queried to enter the rates of crossover and mutation (also known as probability of crossover and mutation).

a) Crossover

Previously paired parents are then combined to produce the offspring. This is done through crossover operators. Each pair produces two offspring after the application of these operators.

b) Mutation

Mutation is simply replacing some genes (i.e. bits) of the chromosome by its logical complement.

Computer Implementation:

- Ask the user for probability of mutation and crossover;
- Implement corresponding crossover and mutation algorithms explained in Chapter 2.

4.3.2.11 Decoding of Genotypes

After the crossover and mutation have been performed, the offspring genotypes are converted into phenotypes based on the number of bits each variable presents through log 10 conversions.

One generation cycle is completed at the end of these operations. The program is run based on the specified number of generations, or until the satisfying criteria is reached.

4.4 SOFTSYS MODELS FOR FULL-DEPTH ASPHALT PAVEMENTS

There are two main backcalculation models developed for SOFTSYS. These are provided in Table 4.1. The first one, FDP-M1, predicts E_{AC} and E_{RI} with the use of information obtained from FWD (D_0, D_{12}, D_{24}, D_{36}) in addition to design thickness of FDP. On the other hand, the second model, FDP-M2, uses deflection information without the need of thickness entry. This model predicts the thickness using FWD deflections only. Both models use the same forward ANN structural model (FWD-FW1), which replaces ILLI-PAVE successfully (the performance of the corresponding ANN model was provided in the previous chapter).

Table 4.1. Parameters (Phenotypes) for Different Types of Pavement Models

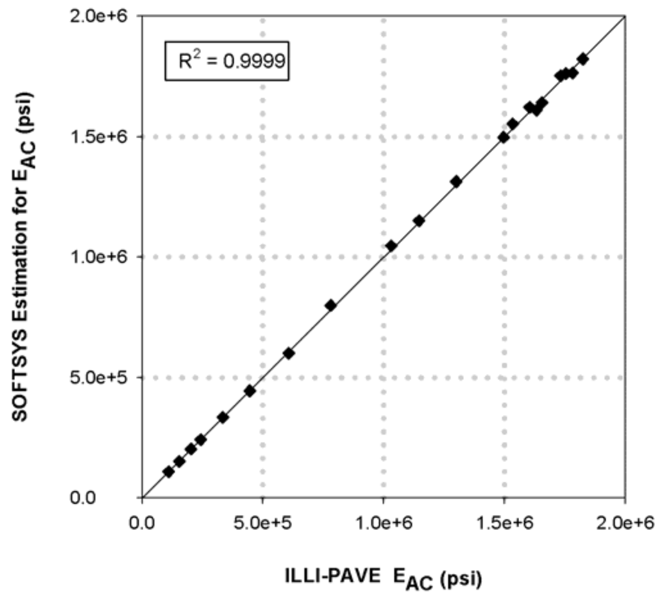
Model Name	Inputs	Outputs
FDP-M1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}	E_{AC}, E_{RI}
FDP-M2	D_0, D_{12}, D_{24}, D_{36}	t_{AC}, E_{AC}, E_{RI}

4.4.1 Performances of Developed SOFTSYS Models

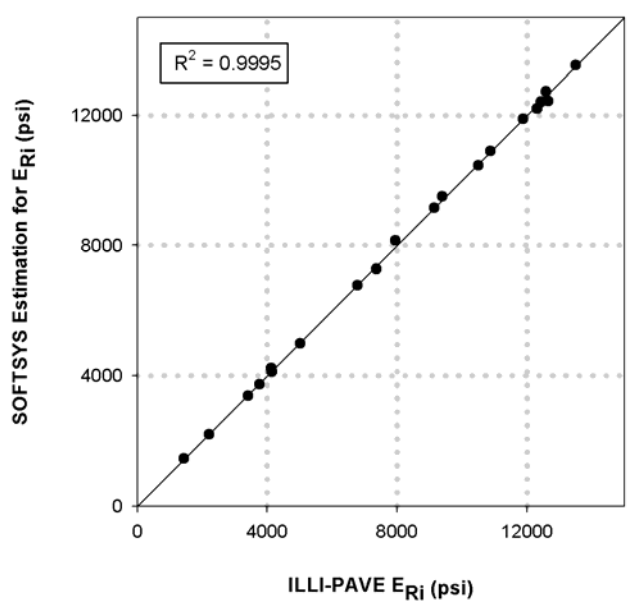
The performances of SOFTSYS models were measured using the synthetic FWD data. For this purpose, 20 stations were selected randomly from the database, created by using the ILLI-PAVE database previously obtained for training ANNs to analyze FDPs. It was named as IP-SYNTH (stands for synthetic ILLI-PAVE) FWD database. IP-SYNTH was analyzed using SOFTSYS models.

Figures 4-3(a) and (b) provide the performance summaries of SOFTSYS FDP-M1 model for predicting pavement layer moduli. The values of correlation coefficients (R^2) being very close to 1 indicate that pavement layer moduli were predicted quite successfully using FDP-M1. In addition, the progress curves of this SOFTSYS model estimations are given in Figures 4-4(a) to (c) for stations randomly selected from IP-SYNTH FWD database. These curves simply represent the growth of member fitnesses of the population through generations. Best fitness (B.F.) values also reported on the progress graphs to show that deflection profile obtained using that member of the population is in conformity with the one in the FWD database. Finally, the growths of the average fitness of the all population members are shown along with the fittest (maximum fitness) and the least fit members (minimum fitness) in the population. All these progress curves are presented to show that no premature convergence was reached during the analyses (Goldberg 1989).

The performance summaries of SOFTSYS FDP-M2 model for predicting pavement layer moduli along with the thicknesses are given in Figures 4-5(a) to (c). The values of correlation coefficients (R^2) being very close to "1" for E_{Ri} indicate that SOFTSYS FDP-M2 worked very effectively to predict breakpoint resilient modulus of the subgrade layer. SOFTSYS was also able to capture the thickness successfully with a correlation coefficient of 0.9791. The prediction of E_{AC} by SOFTSYS produced slightly lower correlation coefficients compared to those reported for the other pavement properties. The best fitness values obtained from FDP-M2 predictions [see Figures 4-6(a) to (c)] for randomly selected stations from the IP-SYNTH FWD database are lower than those of FDP-M1. This is because it is generally much more difficult to predict thicknesses along with the pavement layer moduli.

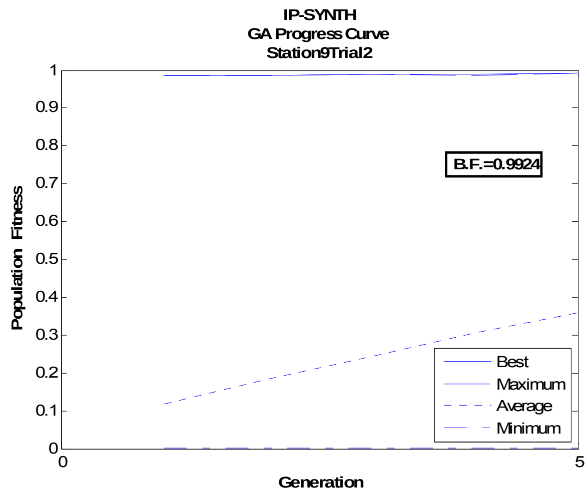


(a) E_{AC}

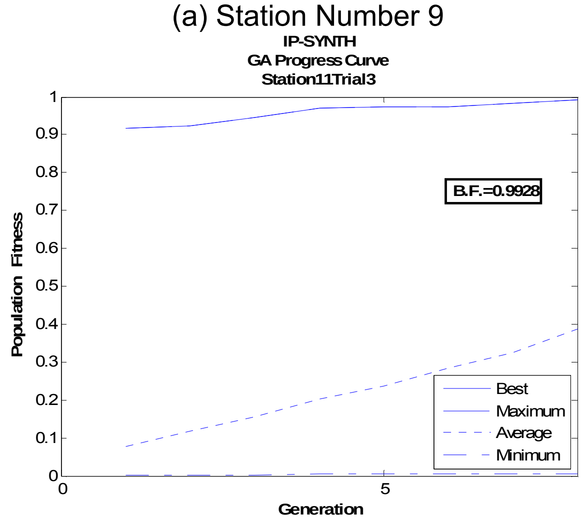


(b) E_{RI}

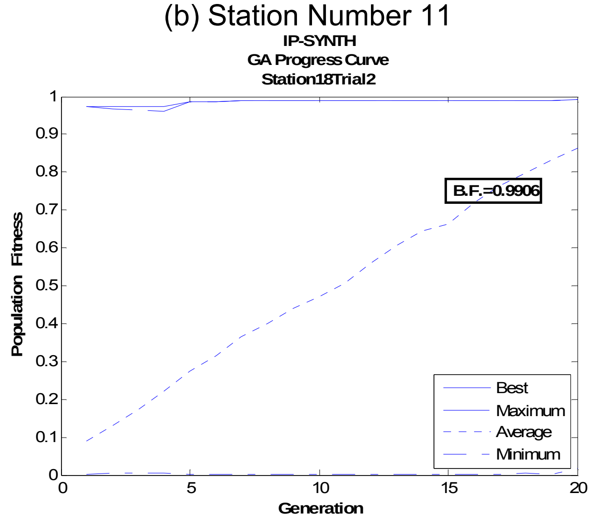
Figure 4-3. SOFTSYS FDP-M1 predictions.



(a) Station Number 9

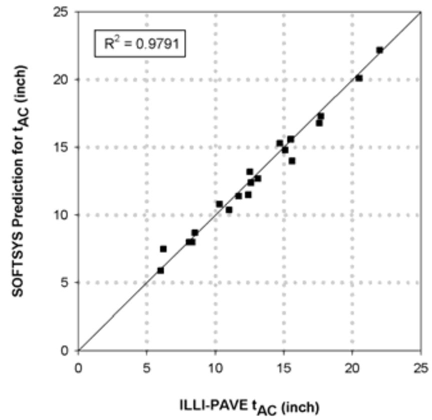


(b) Station Number 11

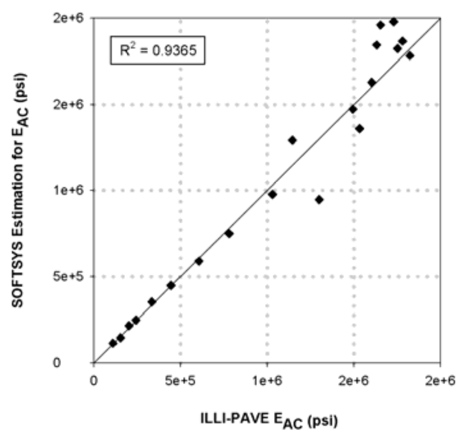


(c) Station Number 18

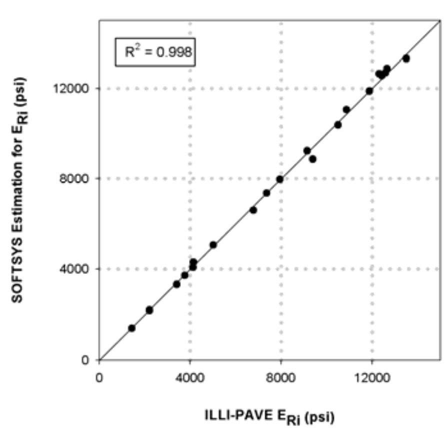
Figure 4-4. Progress curves of SOFTSYS FDP-M1 for randomly selected stations.



(a) t_{AC}

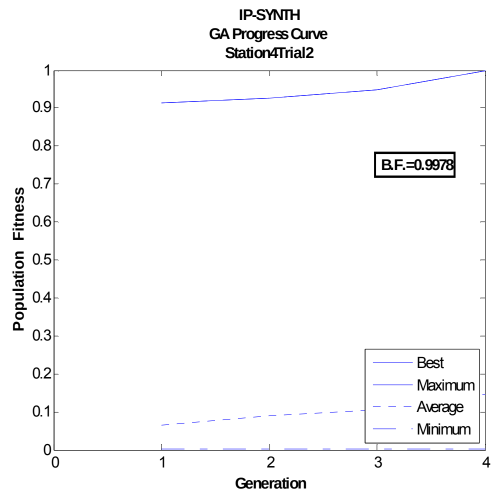


(b) E_{AC}

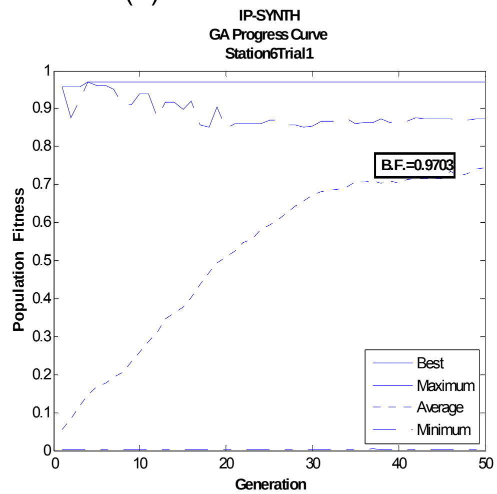


(c) E_{RI}

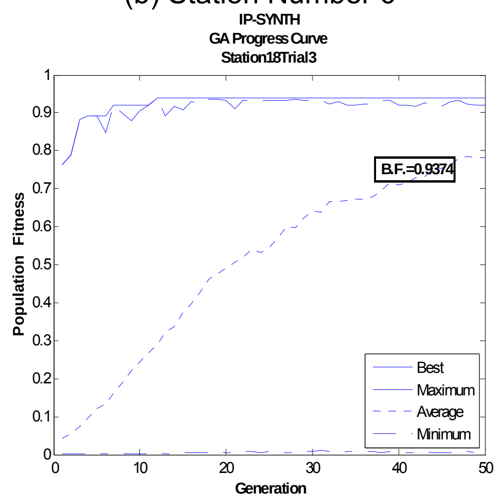
Figure 4-5. SOFTSYS FDP-M2 predictions.



(a) Station Number 4



(b) Station Number 6



(c) Station Number 18

Figure 4-6. Progress curves of SOFTSYS FDP-M2 for randomly selected stations.

4.5. FIELD VALIDATION

4.5.1. Staley Road

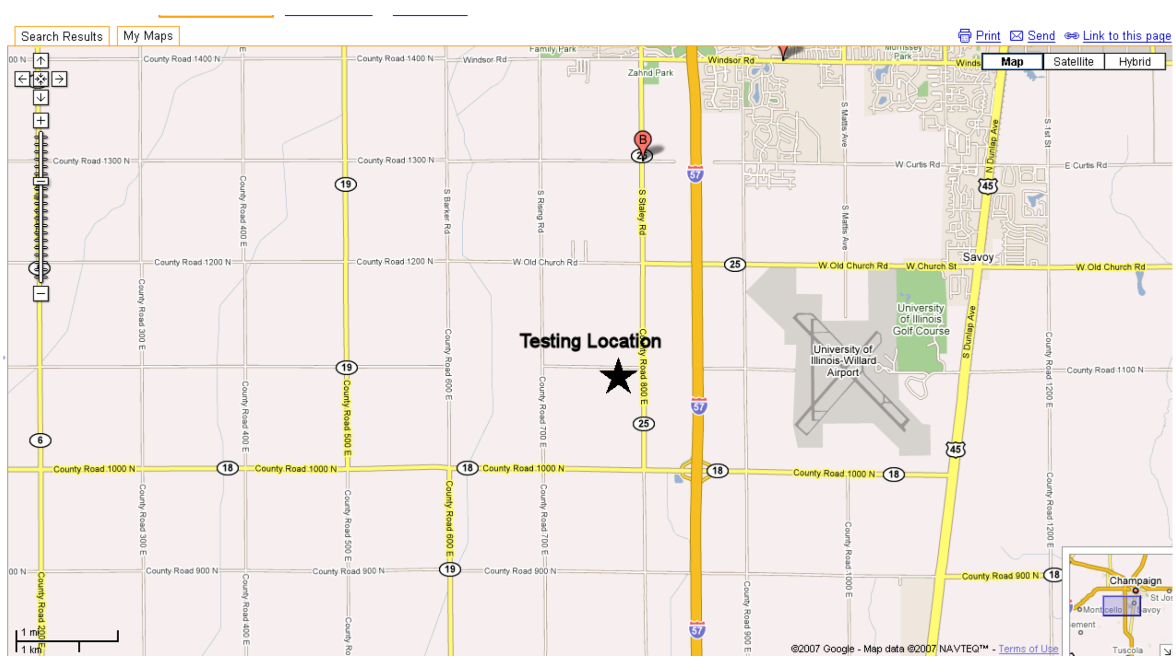
The promising preliminary results obtained with the SOFTSYS approach gave high R^2 values of about 0.97 (equivalent to average absolute error, AAE, values on the order of 6%) for predicting asphalt concrete layer thickness. These results, however, had to be validated with actual field data because the FWD database used in testing the SOFTSYS performance was obtained synthetically. For this purpose, FWD data were collected from Staley Road, in Champaign, Illinois and used for the performance validations of the developed SOFTSYS models. The Staley Road field data included only FWD results along with the temperature information collected in August of 2002, in warm weather conditions. There were, however, no cores taken from the pavement sections at the FWD locations.

As stated in the previous chapter, Staley Road runs in a north-south direction and is located on the west end of the City of Champaign in Champaign County, Illinois [see Figures 4.7(a) and (b)]. The design pavement cross section consists of 12 in. of HMA constructed on LSS with a thickness of 12 in. The FWD tests were performed on about 1,000 ft. of the highway stretch. The pavement temperature was approximately 100^{o}F when the FWD tests were performed. Figure 4-8 shows the locations of FWD testing points along the pavement section. In this figure, the locations of metal plates on the road and reference points are also shown for the sake of completeness.

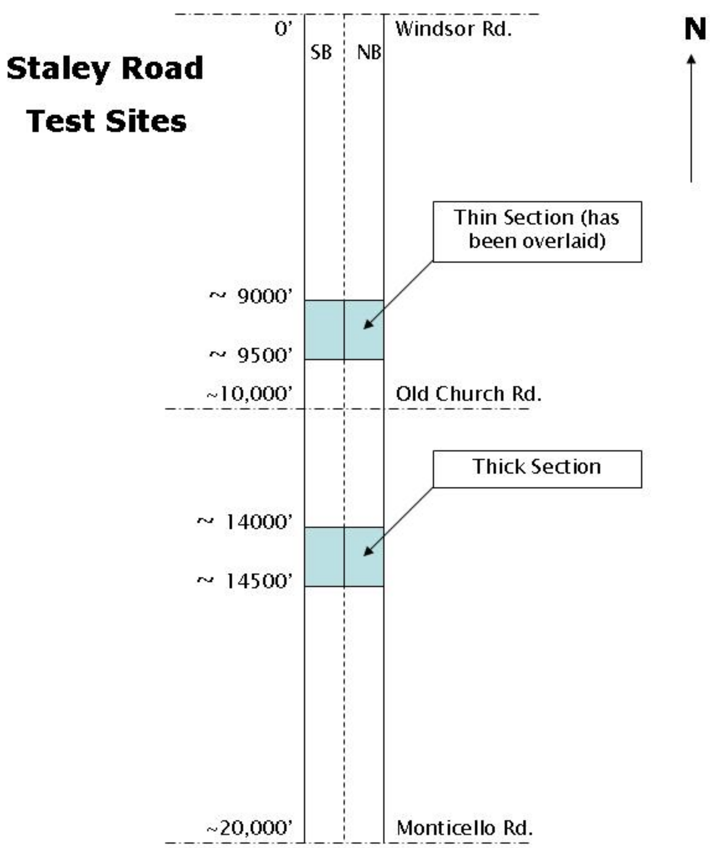
4.5.1.1 GPR testing

GPR technique has been identified as a reliable means to determine thicknesses of pavement sections in the field. In addition to use of GPR, construction thickness data have been obtained to determine pavement thicknesses in the field and establish a database to use in the validation of SOFTSYS pavement thickness predictions. The variability in the field determined or as-constructed thicknesses as well as other pavement layer properties are the critical factors in these validation efforts. Therefore, along with performing FWD tests, GPR testing and field thickness data collection need to be performed on the test sections so that the thickness variations or changes in the construction quality may be effectively assessed from the field data.

Two sets of GPR tests were performed along the Staley road in the same locations where FWD test data were obtained. The details of the GPR tests are provided in Table 4-2. The first set of GPR tests was performed to obtain the asphalt thickness data from the road, and the second one was aimed at verifying the first results and increasing reliability. In the first set of tests, North and South bound lanes of the test section were tested using both ground and air coupled antennae (see Figure 4.9). In the second set of tests, only air coupled antenna was used to verify the previously determined asphalt thickness data. The GPR interpretations for both lanes (right wheel paths) are provided in Figures 4-10 and 4-11. The 1 GHz air antenna was able to capture the HMA and lime stabilized interfaces. However, the 2 GHz air antenna was able to verify the HMA thickness, but not the lime stabilized interface. The interpretation of data collected with the ground coupled antenna did not produce meaningful results, which may be due to several reasons such as noise, or moisture on the surface of the pavement.



(a) Map of Staley Road test location



(b) Layout of Staley Road test sections

Figure 4-7. Location of Staley Road and test sections.

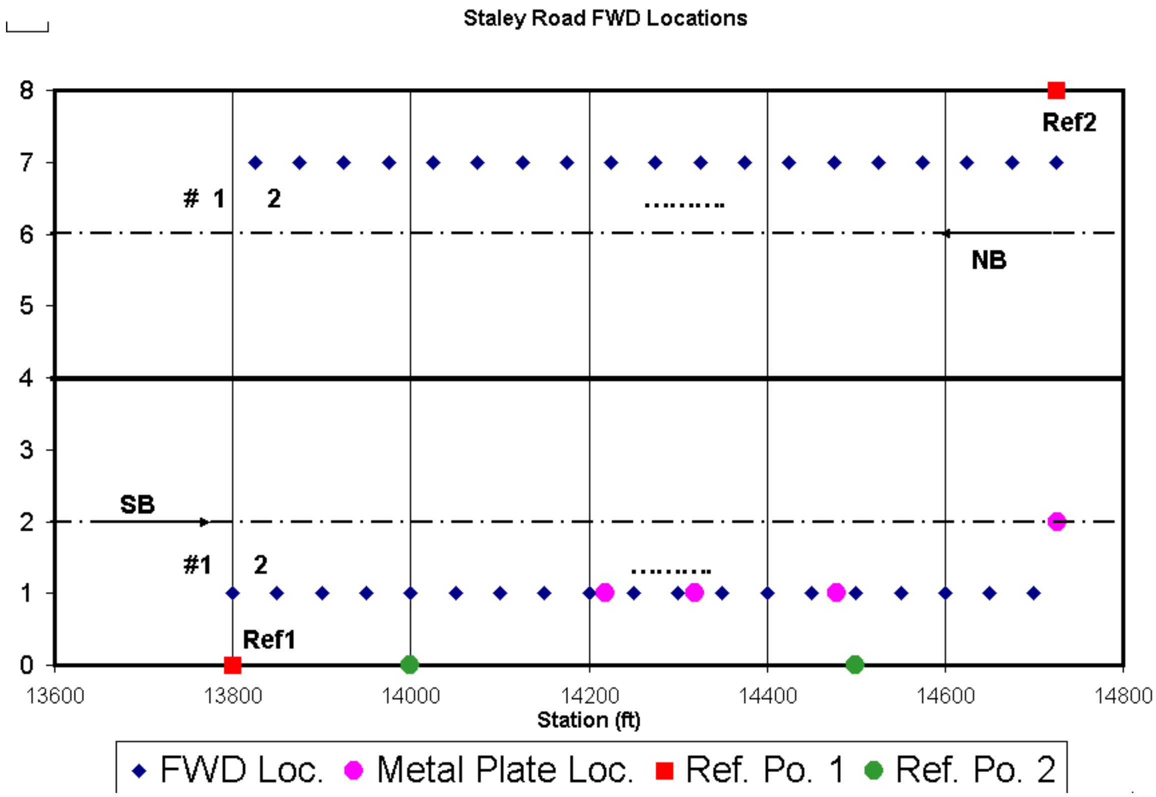
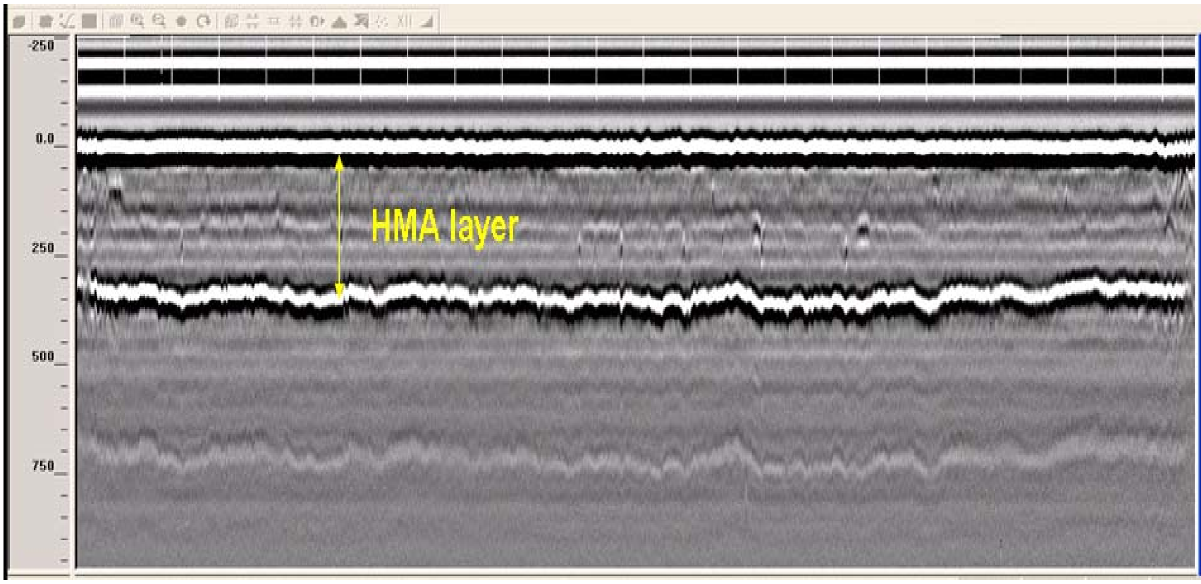


Figure 4-8. Locations of FWD tests along the Staley Road sections.

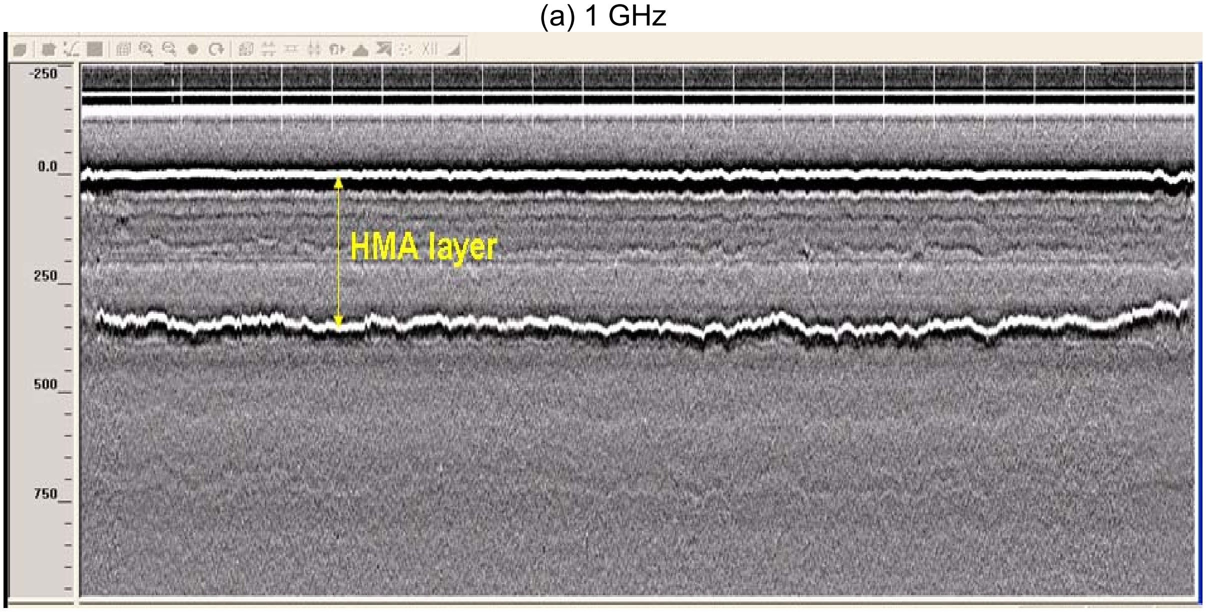
Table 4.2. GPR Test Conditions Along Staley Road Pavement Sections

	Test 1	Test 2
Section	13+800 => 14+750	13+800 => 14+750
Date	November 02, 2008	November 21, 2008
Antenna Used	Ground + Air	Air
Air Condition	Clear (No rain 3 days before testing)	Clear (No rain 3 days before testing)

Figure 4-9. Air and ground coupled antennae used in GPR testing.

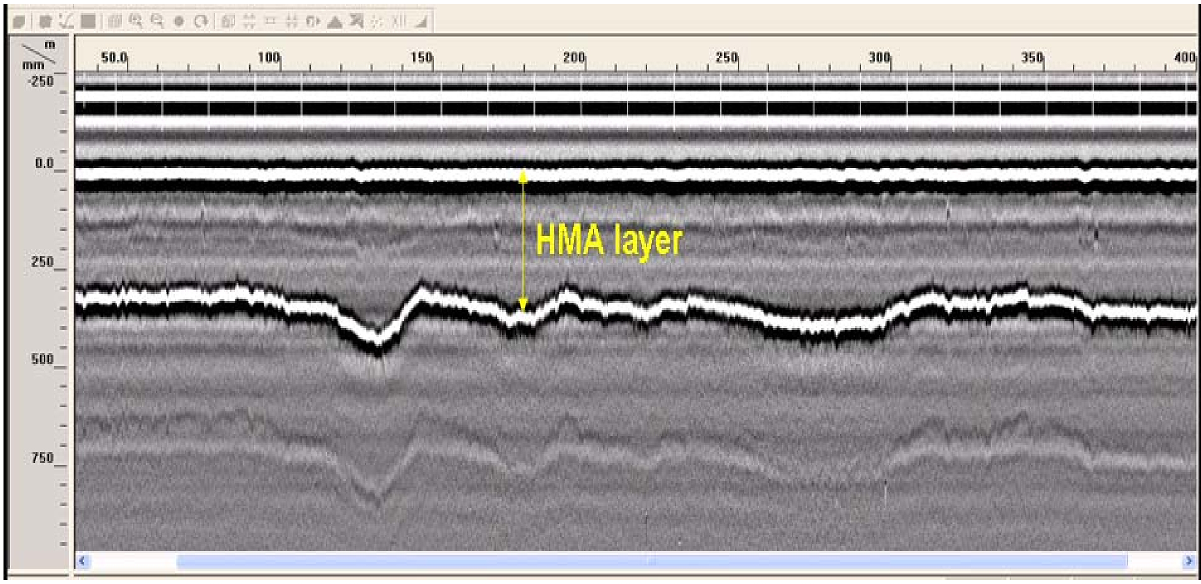


(a) 1 GHz

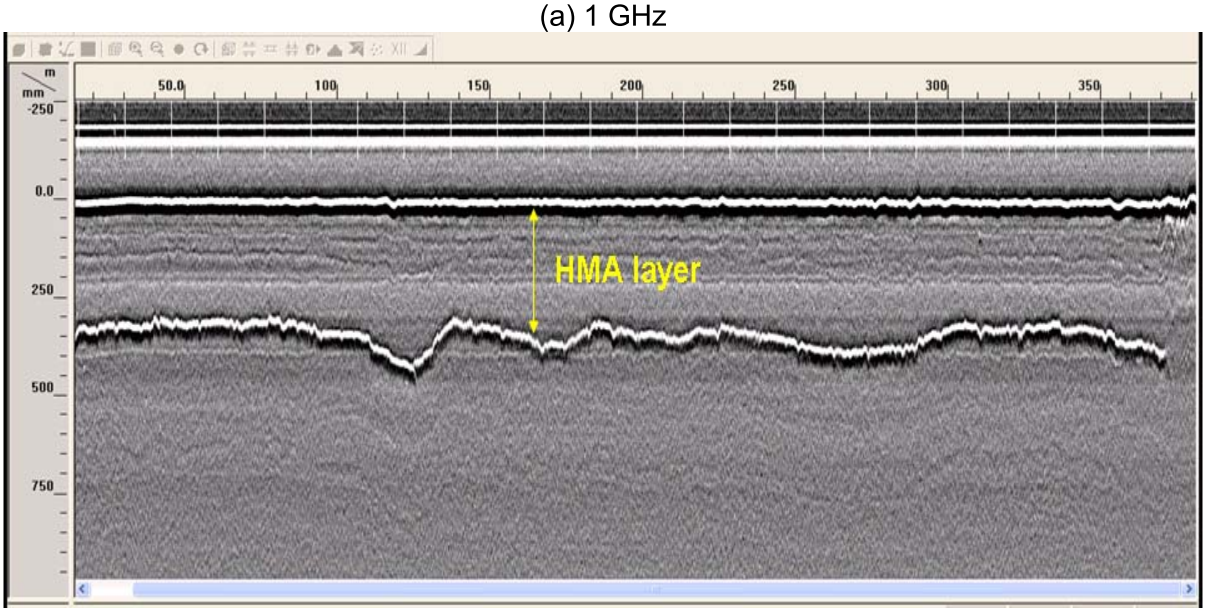


(b) 2 GHz

Figure 4-10. GPR test results: north bound right wheel path.



(a) 1 GHz



(b) 2 GHz

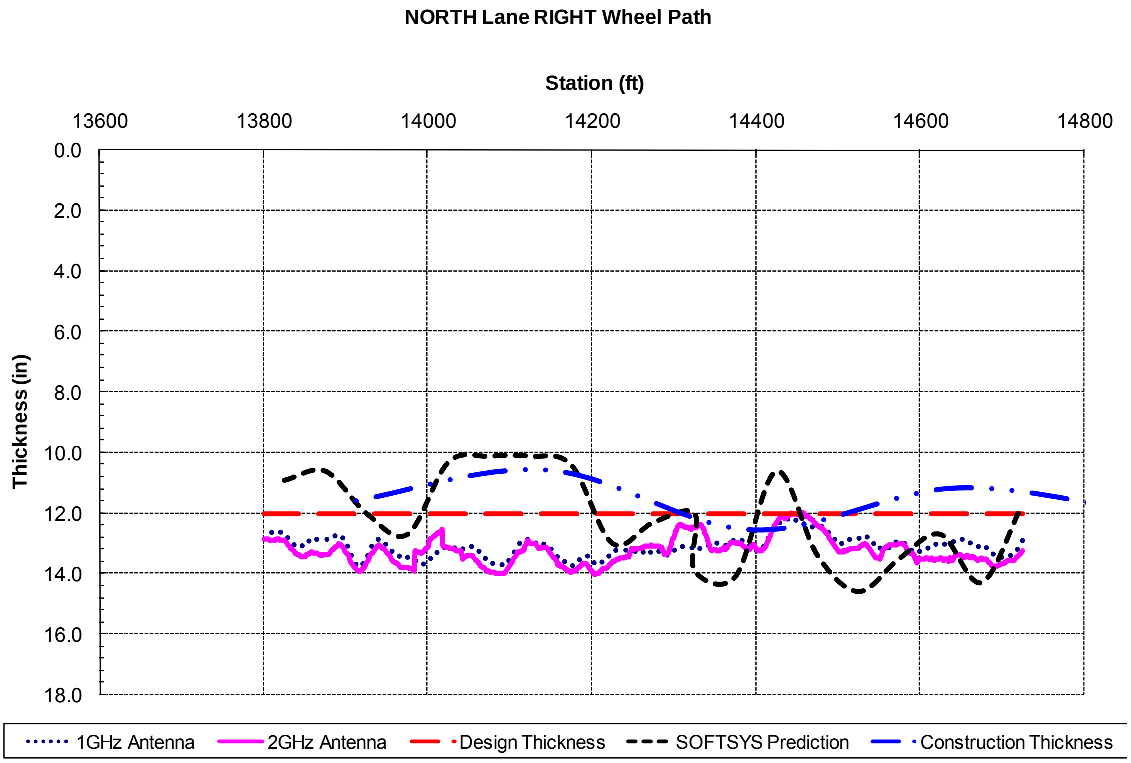
Figure 4-11. GPR test results: south bound right wheel path.

4.5.1.2 SOFTSYS Analyses

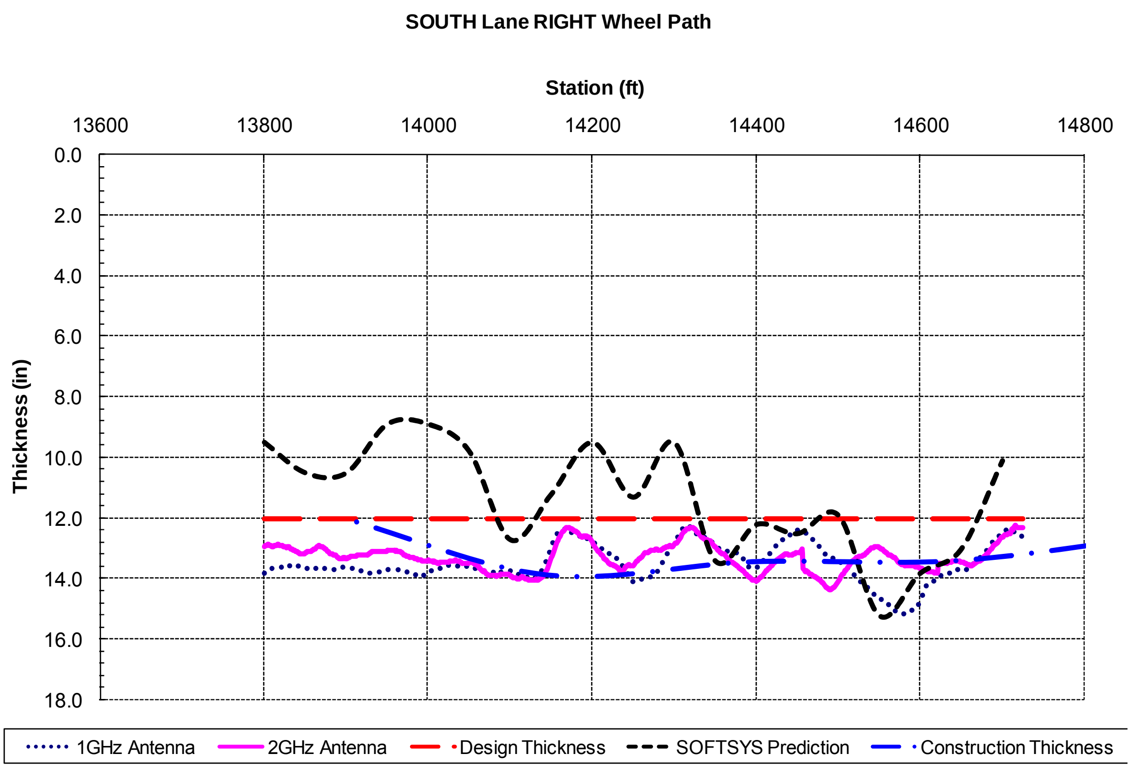
The data obtained from GPR indicated that the constructed pavement thickness was generally thicker than the design thickness (by approximately one inch) although there were sections that were even thinner than the design thickness. The thickness data from the field were deemed to be essential to calibrate the GPR test results. For this purpose, the elevation data were obtained from the time when the road was constructed. There were three observation points identified within the pavement section where FWD tests were performed. These elevation points were then used to sufficiently compare GPR test results. Finally, the SOFTSYS predictions were also compared with the thickness data both from GPR testing and the construction thicknesses to validate the thickness finder portion of the SOFTSYS program. No temperature correction was included in backcalculation of pavement layer properties.

Figures 4-12 (a) to (d) provide the thickness estimations of SOFTSYS from the FWD data together with the thicknesses obtained from both GPR and construction survey data. The thicknesses obtained using SOFTSYS captured construction data well on the North lane [see Figure 4-12 (a)]. However, SOFTSYS generally predicted lower thicknesses on the South lane [see Figure 4.12 (b)]. The SOFTSYS predictions for both E_{AC} and E_{Ri} are also given in Figures 4-12 (c) and (d), respectively.

In an attempt to further verify the SOFTSYS results, another model was developed to take into account the LSS layer (named FDP-LSS M2) since Staley road was built on lime modified soil. The predictions are given in Figures 4-13 (a) to (g). Similar to the ones obtained from FDP-M2 model, the thicknesses obtained using FDP-LSS M2, were in good agreement with the construction data on the North lane [see Figure 4-13 (a)]. On the other hand, SOFTSYS generally predicted lower thicknesses on the South lane [see Figure 4-13 (b)]. The lime stabilized section thicknesses are also given in Figures 4-13 (c) and (d). Since no information is given on the actual LSS thicknesses, the predictions are given in comparison to design thicknesses of the LSS layer. SOFTSYS predicted LSS layer thicknesses with reasonable accuracy. Although the results showed variability, the thicknesses predicted remained in the range of 10 to 13 in., which are somewhat realistic considering the typical thickness variability of LSS layers is more than that of HMA. Finally, the SOFTSYS estimations for E_{AC}, E_{LSS}, and E_{Ri} are also given in Figures 4-13 (e) to (g), respectively. In general, the variations of AC and LSS layer thicknesses observed were attributed to the variations of the FWD test data.

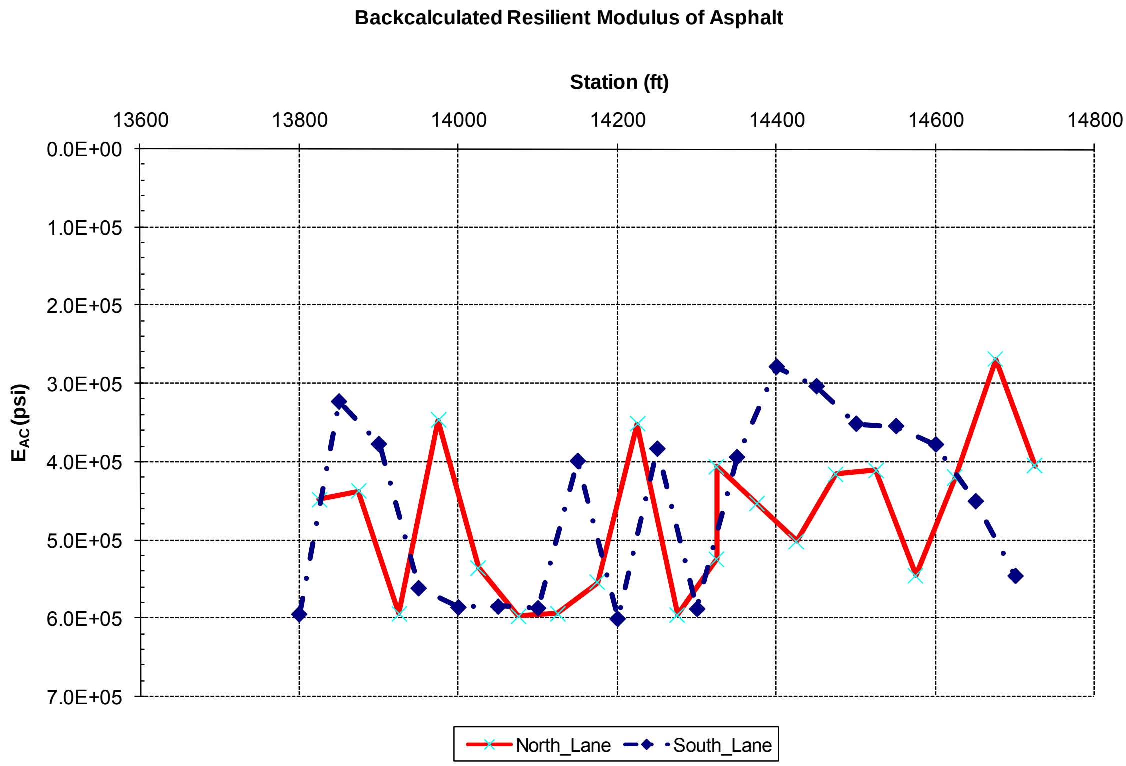


(a) t_{AC} northbound

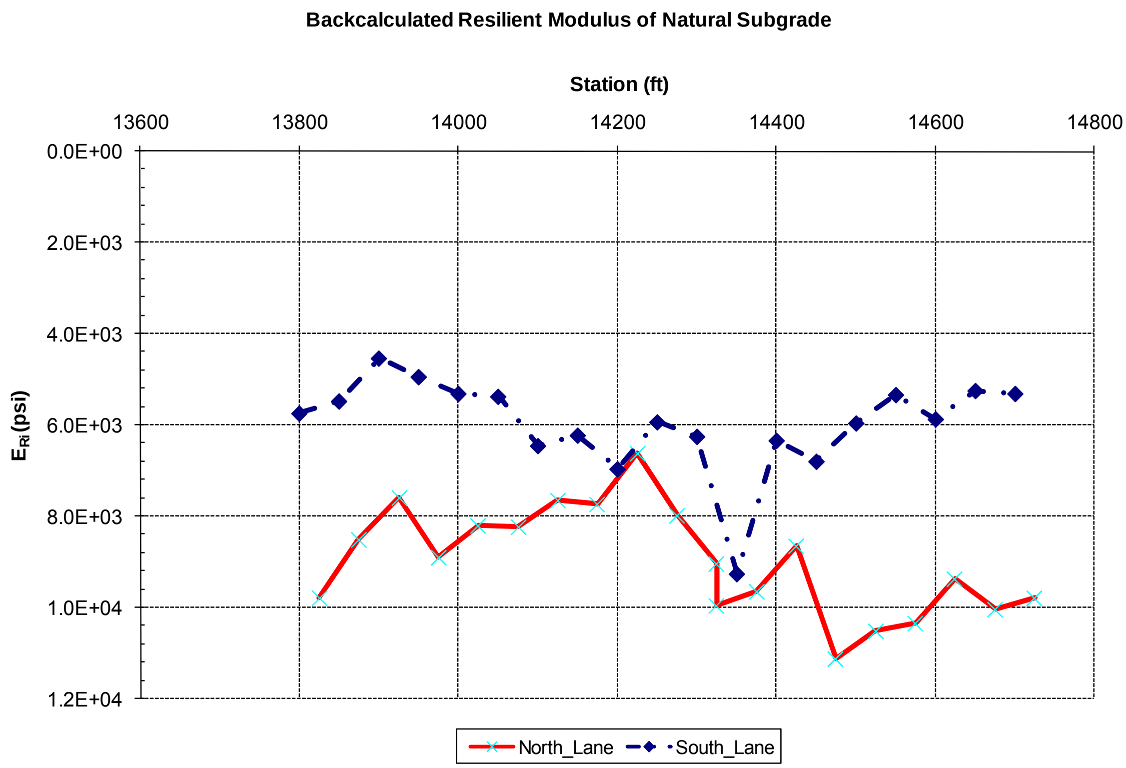


(b) t_{AC} southbound

Figure 4-12. Estimation of pavement layer properties using SOFTSYS FDP-M1.

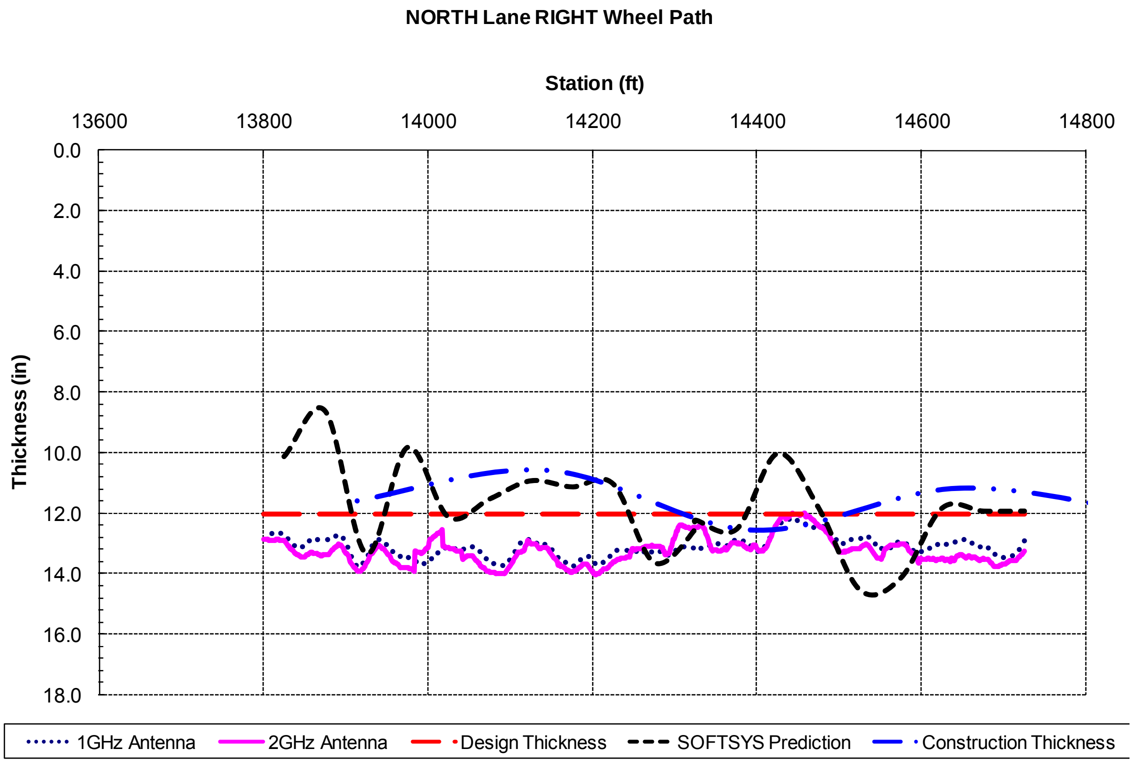


(c) E_{AC}

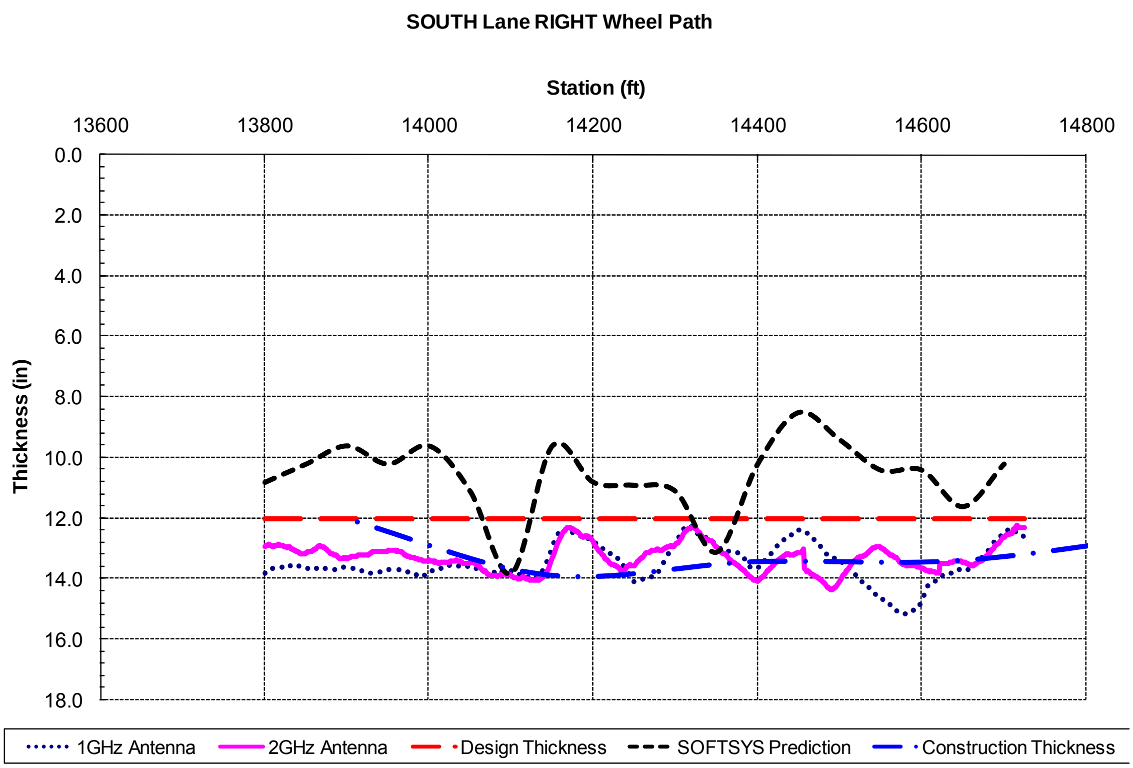


(d) E_{Ri}

Figure 4-12. Estimation of pavement layer properties using SOFTSYS FDP-M1 (contd.).

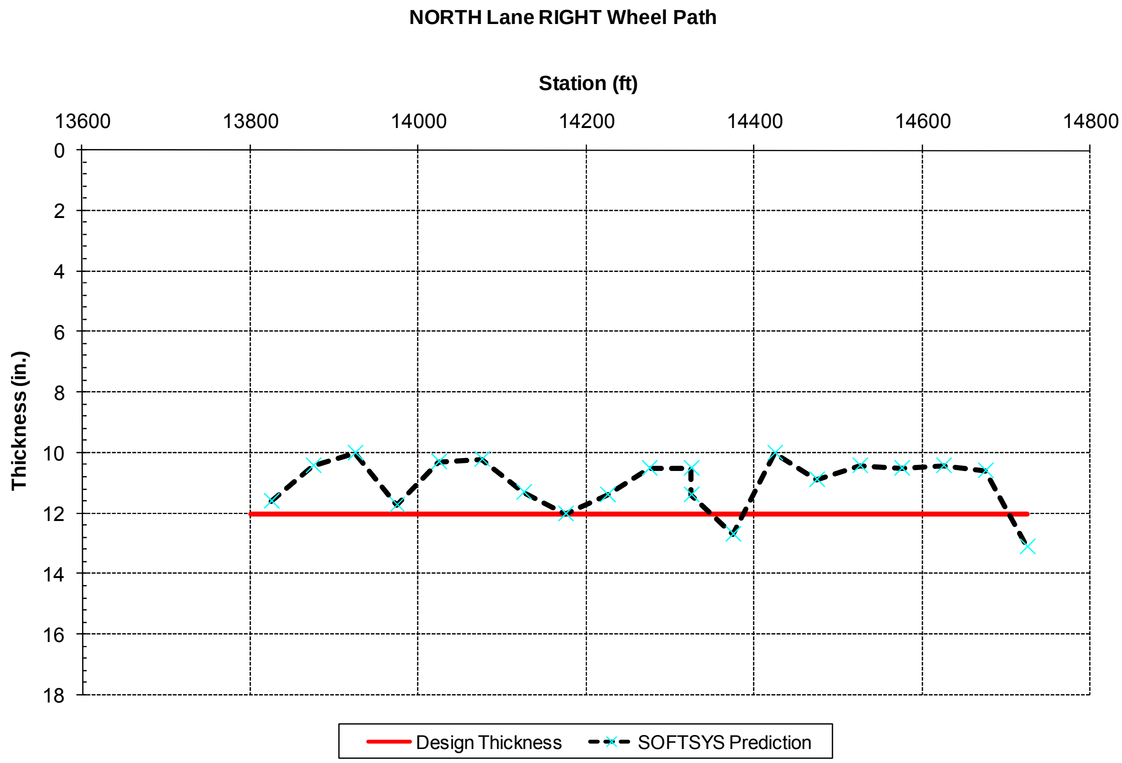


(a) t_{AC} northbound

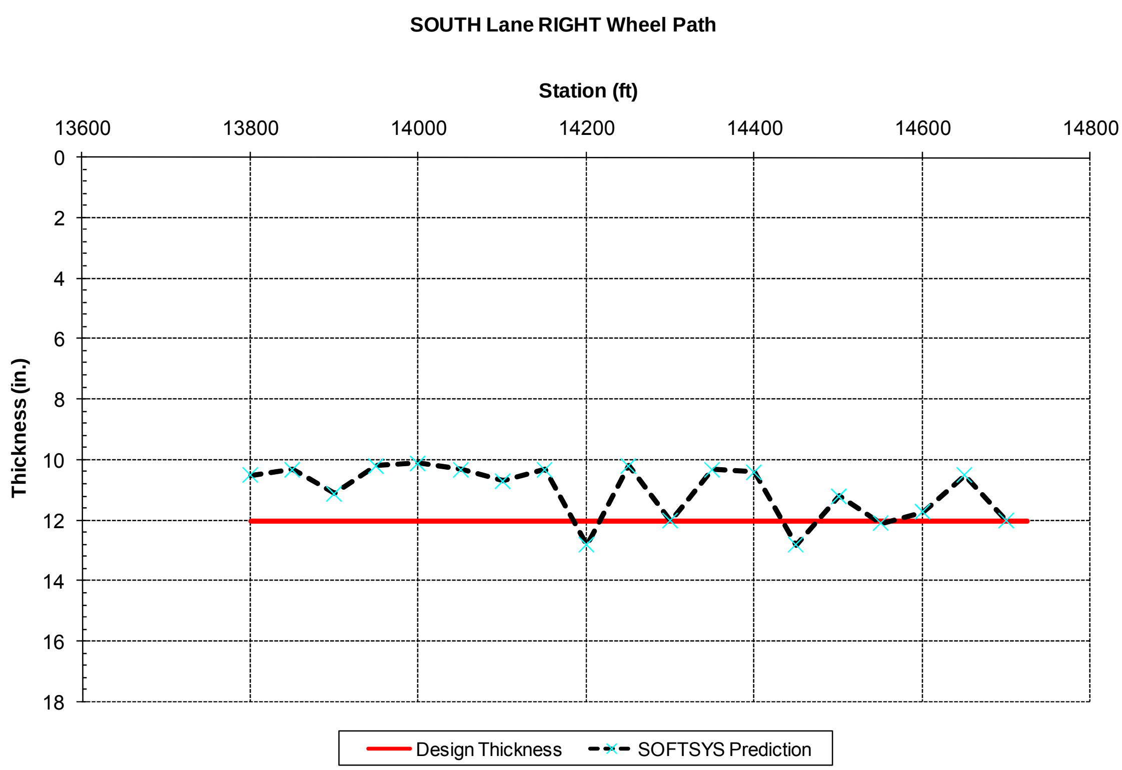


(b) t_{AC} southbound

Figure 4-13. Estimation of pavement layer properties using SOFTSYS FDP-LSS M2.

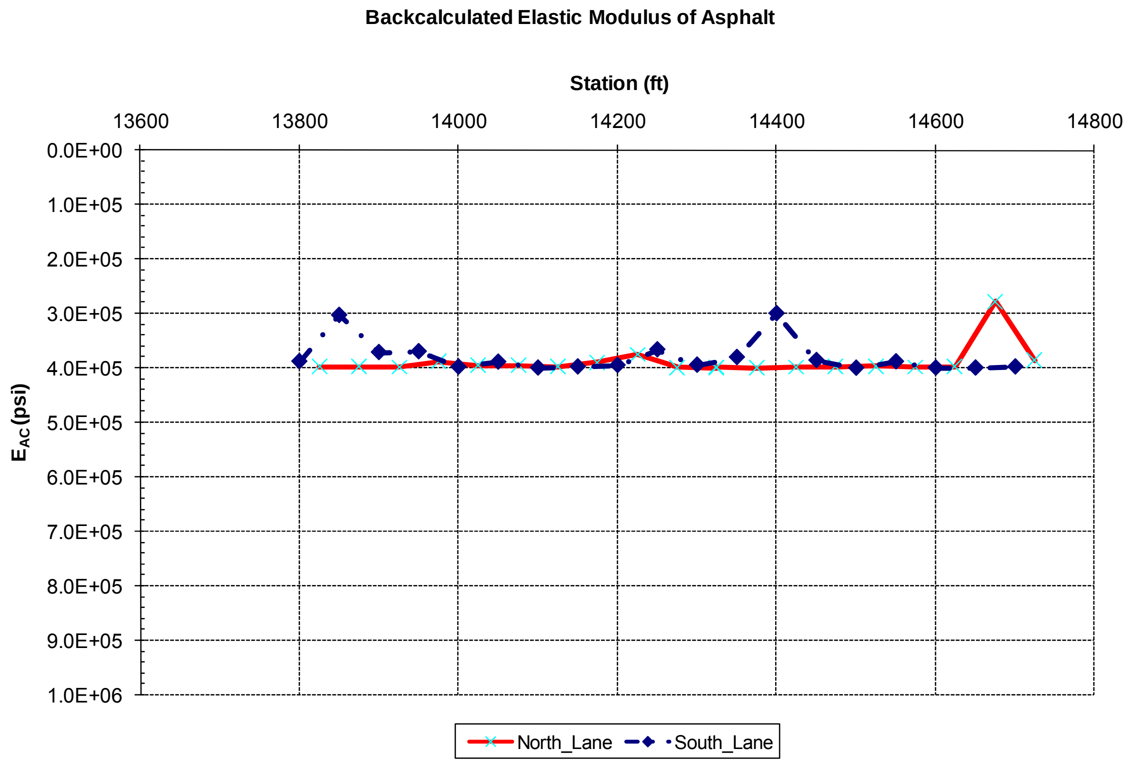


(c) t_{LSS} northbound

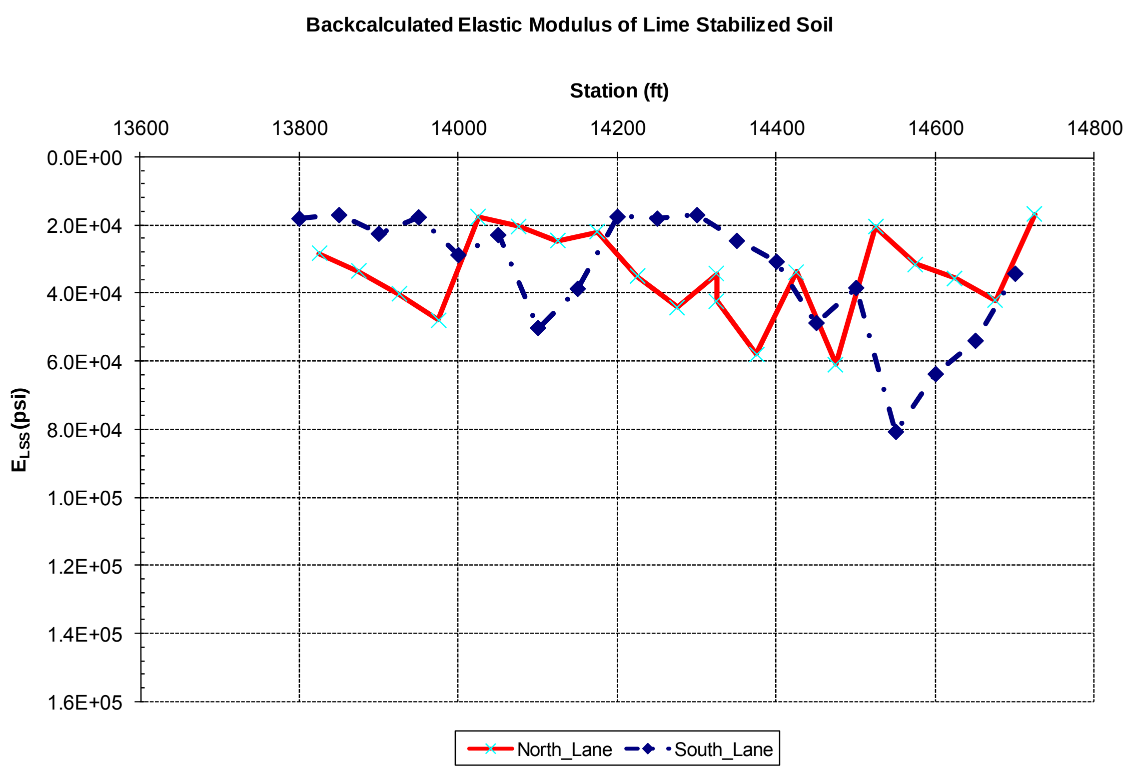


(d) t_{LSS} southbound

Figure 4-13. Estimation of pavement layer properties using SOFTSYS FDP-LSS M2 (contd.).

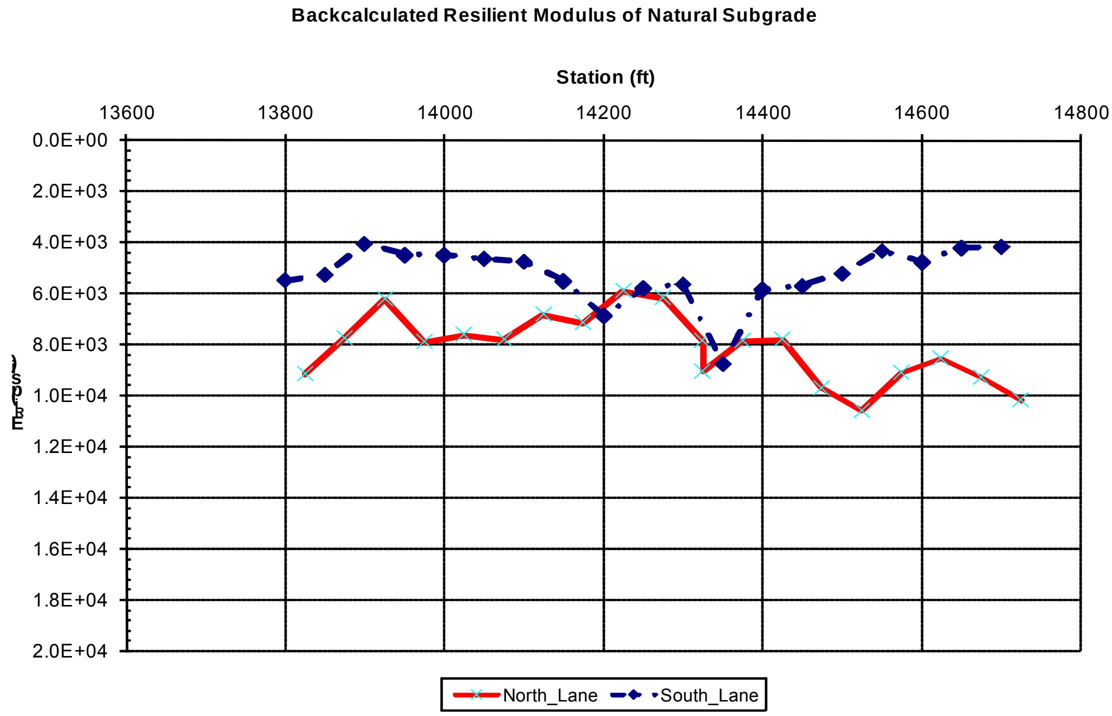


(e) E_{AC}



(f) E_{LSS}

Figure 4-13. Estimation of pavement layer properties using SOFTSYS FDP-LSS M2 (contd.).



(g) E_{Ri}

Figure 4-13. Estimation of pavement layer properties using SOFTSYS FDP-LSS M2 (contd.).

CHAPTER 5: SUMMARY AND CONCLUSIONS

5.1 SUMMARY

Pavement condition assessment in the field conducted by the use of Falling Weight Deflectometer (FWD) often requires the use of linear elastic pavement layered analysis tools to backcalculate layer moduli. However, both the subgrade soils and unbound aggregate base/subbase layers exhibit nonlinear, stress dependent geomaterial behavior. Sophisticated pavement structural models are needed to perform nonlinear analyses for more accurate solutions with fast computation schemes. This study focused on the use of artificial neural network (ANN) pavement structural models developed with the results of the ILLI-PAVE finite element (FE) program for FWD backcalculation and prediction of pavement critical responses. In addition, it has also focused on the hybrid use of Genetic Algorithms (GAs) and ANNs to estimate the pavement layer properties including hot-mix asphalt concrete (HMA) thickness using only the FWD test data on full-depth asphalt pavements.

First, information was collected on the types, and typical geometries and layer properties of different flexible pavements existing in the State of Illinois. This information was crucial for conducting many ILLI-PAVE FE analyses of typical pavement geometries and layer material properties and creating the synthetic pavement deflection basin data which represented the response/behavior of Illinois flexible pavements.

Then, the ILLI-PAVE finite element program, extensively tested and validated for over three decades, was used as an advanced structural model for solving deflection profiles and responses of the identified typical Illinois flexible pavements including Full-Depth Asphalt Pavements, Full-Depth Asphalt Pavements on Lime Stabilized Soils, Conventional Flexible Pavements, and Conventional Flexible Pavements built on Lime Stabilized Soils. Pavement deflection basins were created by the ILLI-PAVE FE runs under the standard 9,000-lb FWD loading. Pavement deflection and response databases established from the ILLI-PAVE FE solutions in this manner covered all combinations of the different pavement geometries, layer thicknesses, and layer moduli.

Using these databases, both forward and backcalculation types of ANN models were developed. Different ANN model network architectures were searched and trained to determine the optimum architectures that best captured the behavior of the Illinois pavement sections. In each case, a portion of the ANN model training data was separated as an independent testing set to check the performance of the trained ANN architecture. Several different network architectures were trained using different number of input parameters. Some of the network architectures were designed for directly predicting the critical pavement responses, such as the maximum horizontal tensile strain at the bottom of HMA layer or the vertical stress/strain on top of subgrade, from the FWD deflection basins. These networks have been crucial for implementing the mechanistic based pavement design and validating extended life HMA design concepts.

In an effort to validate ANN backcalculation models, FWD test data already available at the IDOT Bureau of Materials and Physical Research from previous Illinois Highway Research (IHR) studies were collected for establishing a comprehensive field FWD database from pavements in Illinois, with known layer thicknesses and material properties. Examples of such previous studies with available FWD test data are the High Cross Road, Roseville Bypass, Staley Road, US 50, US 20, and Sand Pit Road projects. The validation database established this way from the field FWD data was fully utilized in a comprehensive effort to validate the ANN models developed for robustness and accuracy in predicting the pavement layer moduli and critical pavement responses directly from FWD testing. In addition, results of extensive FWD tests also conducted on the University of Illinois Advanced Transportation Research and Engineering Laboratory (ATREL) pavement sections under ICT-R39 project and on other Illinois in-service pavements by the IDOT nondestructive evaluation team were also used as the field validation data.

During the development of the ANN models, a professional ANN (ANN-Pro) toolbox was prepared as user-friendly software with a graphical user interface (GUI) to enable easy inputting of the FWD deflection data with pavement layer thicknesses and outputting of the ANN model predictions for forward and backcalculation structural analyses. The toolbox software was updated in a way that it directly reads the FWD deflection data from the FWD testing equipment and prints the pavement layer moduli and critical pavement response predictions in real time as the program output.

In addition, the framework SOFTSYS, which stands for Soft Computing Based Pavement and Geomaterial System Analyzer, was developed as a new pavement analyzer by the research team to perform both forward and backcalculation analyses by the hybrid use of GA and ANN models thus enabling full-depth asphalt pavement analyses without knowing the HMA layer thickness. Similar to the ANN models, SOFTSYS performance needed to be validated with the actual field data. Ground Penetrating Radar (GPR) was selected as the most reliable way of determining layer thicknesses of medium to long stretches of field pavement sections. In addition, construction thickness data were also required to determine the thicknesses of in-service pavements. The variability in the thickness as well as other pavement properties was a critical issue. Therefore, along with the FWD testing, GPR testing was also conducted to obtain pavement thickness data. The SOFTSYS thickness predictions were then successfully validated through comparisons with the GPR test results and pavement section construction thickness data.

5.2 CONCLUSIONS

A suite of ANN models (available in the accompanying ANN-Pro software program) developed in this study for the analyses of full-depth asphalt and conventional flexible pavements, built on both natural and lime stabilized subgrades, proved that ANN model predictions for the backcalculated layer moduli and the critical pavement responses, i.e., the maximum horizontal tensile strain at the bottom of HMA layer responsible for fatigue and the vertical stress/strain on top of subgrade responsible for subgrade rutting conditions, were within very low average absolute errors of those obtained directly from the ILLI-PAVE FE solutions. Further, the excellent performances of the developed surrogate ANN structural models (forward models) proved that they could be used in lieu of finite element analyses for the quick and accurate predictions of the surface deflections and the critical responses of all types of full-depth and conventional flexible pavements found/constructed in Illinois.

The results of pavement structural modeling with the ILLI-PAVE FE program showed that improvements due to the constructed lime stabilized subgrade soil layer had to be captured separately in the analyses since there are significant differences between the critical pavement responses of full-depth pavements, widely constructed and found as high volume Interstate highways in Illinois, on unmodified subgrade and lime stabilized subgrade. Therefore, for correctly modeling the pavement response and behavior with the lime stabilized subgrade soil layer, separate forward and backcalculation analysis approaches were developed to accurately predict pavement deflection profiles and pavement critical responses under FWD loading.

The performances of ANN models developed for lime stabilized sections were validated with the field FWD data collected from three highway projects in Illinois. In addition, FWD data collected from other pavement test sections in Illinois, at the University of Illinois ATREL, and Henry County test site were also used for field validation purposes. Low average absolute errors obtained when compared to ILLI-PAVE base algorithms currently in use proved that ANN models could be used reliably to backcalculate layer moduli of flexible pavements built on both lime stabilized and natural subgrades. When compared with regression based backcalculation algorithms for no lime full-depth asphalt pavements, the developed ANN models justifiably predicted higher subgrade moduli corresponding to much lower wheel load deviator stresses found under the lime stabilized layer.

In conclusion, ANN models did not require the knowledge of advanced material property inputs, and therefore, can be effectively used through the implementation of ANN-Pro software program as quick and reliable backcalculation tools for the nondestructive evaluation of flexible pavements in Illinois.

Thickness variability was a real issue in the field, and coring was not always an option to determine layer thickness. The SOFTSYS, Soft Computing Based Pavement and Geomaterial System Analyzer, framework was developed as another project deliverable software package to backcalculate layer moduli and predict HMA thicknesses of full-depth asphalt pavements. SOFTSYS was shown to work effectively with the synthetic data obtained from ILLI-PAVE FE solutions. The very promising SOFTSYS software results obtained indicated average absolute errors (AAEs) on the order of 6% for the HMA thickness estimation.

The field validations of SOFTSYS with Staley Road FWD data also produced meaningful results. Higher deflection values did correlate well with thinner backcalculated HMA thicknesses. In addition, the thickness data obtained from GPR testing matched reasonably well with that of SOFTSYS results although in some locations the maximum difference between the two results was up to 3 in. The variations of HMA and lime stabilized soil layer thicknesses observed were attributed to variations of FWD data. The data obtained from GPR indicated that the constructed HMA thicknesses were generally greater than the design thickness (by approximately 1 in.) although there were sections that were even thinner than the design thickness. The thickness data from the field were deemed to be essential to calibrate the GPR test results.

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APPENDIX A

Artificial Neural Network Software for Professionals
ANN-Pro
Version 1.0.0.0

User's Manual

CONTENTS

CHAPTER 1: INTRODUCTION

Artificial neural network software for professionals (ANN-Pro) is a user interface written for engineers actively involved in backcalculation of pavement layer properties using the data obtained from a Falling Weight Deflectometer (FWD) test. It is a complete toolbox developed as the final product of R39-2 project, “Nondestructive Pavement Evaluation Using ILLI-PAVE Based Artificial Neural Network Models”, funded by Illinois Department of Transportation (IDOT) through the Illinois Center for Transportation research activities.

ANN-Pro software is a deliverable of the R39-2 project intended to bring research findings into engineering practice. The background information on Artificial Neural Networks (ANNs), FWD test and pavement layer backcalculation can be found in the main technical report of this project. ANN-Pro software aims to assess the structural condition of an existing pavement by analyzing FWD data. The software allows users to conduct advanced pavement structural analyses, similar to ILLI-PAVE finite element (FE) analyses, for validating IDOT’s mechanistic pavement analysis and design concepts with special emphasis on extended life hot-mix asphalt (HMA) designs.

The objective of this manual is to make users familiar with many practical features of this comprehensive toolbox. Accordingly, this manual provides guidance and details about the operation of ANN-Pro. In addition, users are introduced with advanced software features aimed to increase the efficiency while using the software.

The coding of ANN-Pro was initiated when R39-2 project started in 2004. The mainframe was finished in about two years. Since then the software has been continuously updated based on the feedback received from IDOT engineers. The software’s final version 1.0.0.0, described in this Manual, has been submitted to IDOT as a project deliverable.

DISCLAIMER

This software is based on the results of R39-2, Nondestructive Pavement Evaluation Using ILLI-PAVE-Based Artificial Neural Networks. R39-2 is conducted in cooperation with the Illinois Department of Transportation, Division of Highways, and the U. S. Department of Transportation, Federal Highway Administration.

The contents of this software reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views or policies of the Illinois Department of Transportation or the Federal Highway Administration. This software does not constitute a standard, specification, or regulation.

SOFTWARE REQUIREMENTS

ANN-Pro was developed for computers running in MS Windows environment. It was originally intended to operate in Windows XP operating system considering its availability in IDOT’s computers. However, with the introduction of Windows Vista operating system in 2007, ANN-Pro was modified to work in both operating systems. Adaptation to newer operating systems that may appear on the market in the future can be assured with very minor modifications.

ANN-Pro was developed using object oriented programming (OOP). The coding was done using Borland Delphi 7, which is also known as object Pascal. In addition, powerful Delphi components were effectively utilized for better visualization and functionality of the program.

HARDWARE REQUIREMENTS

ANN-Pro was developed to run efficiently without allocating memory resources of a computer. Although lower speed processors may be feasible, an Intel Pentium III processor with 667 MHz clock speed is suggested as the minimum for practical purposes. Naturally, the older the system is, it takes longer to setup the software or to run analyses. Therefore, it is also suggested that the user have recently manufactured processor to have agreeably faster operations with the software. In addition, a minimum 512 KB of randomized memory (RAM) is recommended for effective use of the software. Finally, advanced visualization features in the software were developed using the Delphi components. The visual effects, however, are very much dependent on how Windows tools are shown by adjusting display properties on the screen. There is no requirement for a specific graphics processor. The minimum screen resolution is recommended as 800 x 600 pixels.

PROGRAM SETUP

The program is distributed with a setup file. This file is zipped and will be provided separately for each distribution. First, the user needs to log in the computer with an administrative account in order to set up the software. Otherwise, the setup process will not be completed successfully. The zipped file needs to be opened into any existing folder. If any older version of the software is already installed, it first must be installed. Double clicking on the setup file will initiate the setup process (see Figure 1-1). The steps are then relatively straight forward to follow since the setup is automatically created by Delphi program. Although installation steps are self explanatory, Figures 1-2 through 1-7 show details of the individual steps for the sake of completeness.

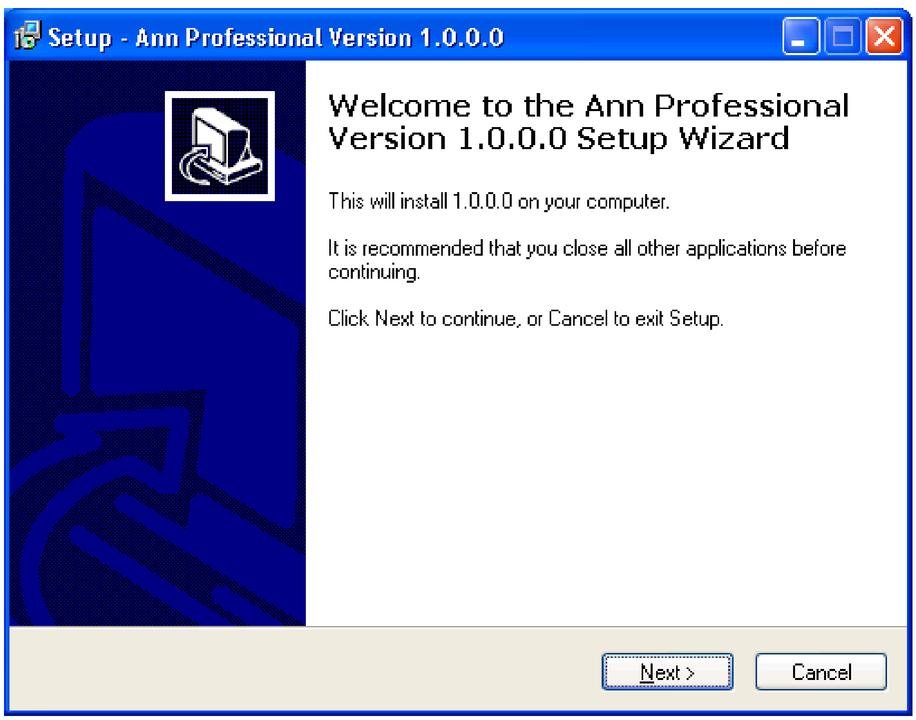


Figure 1-1. Setup welcome screen.

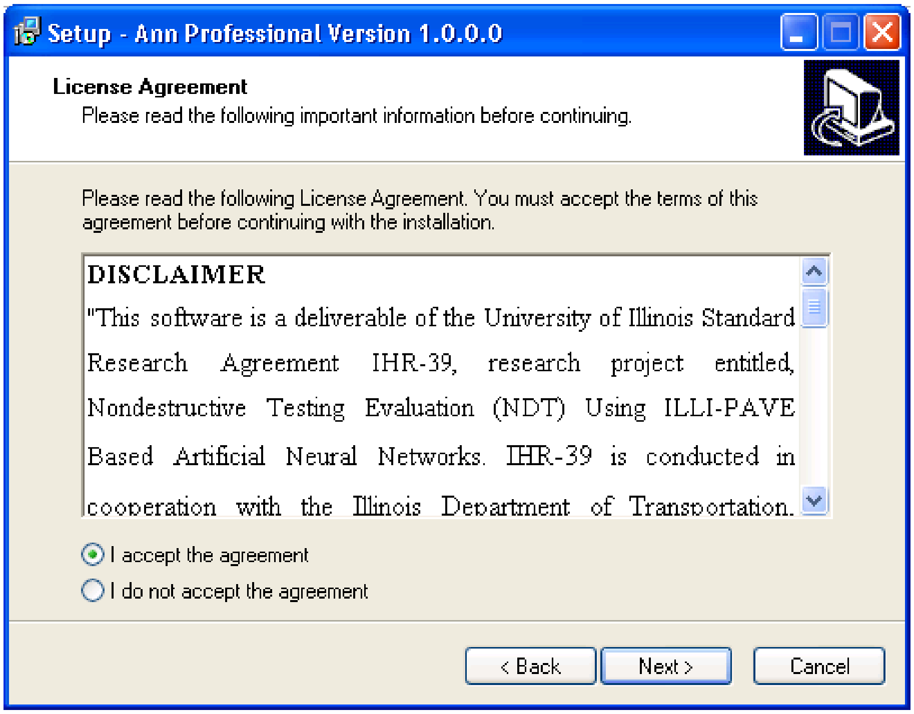


Figure 1-2. Disclaimer – license Agreement for ANN-Pro.

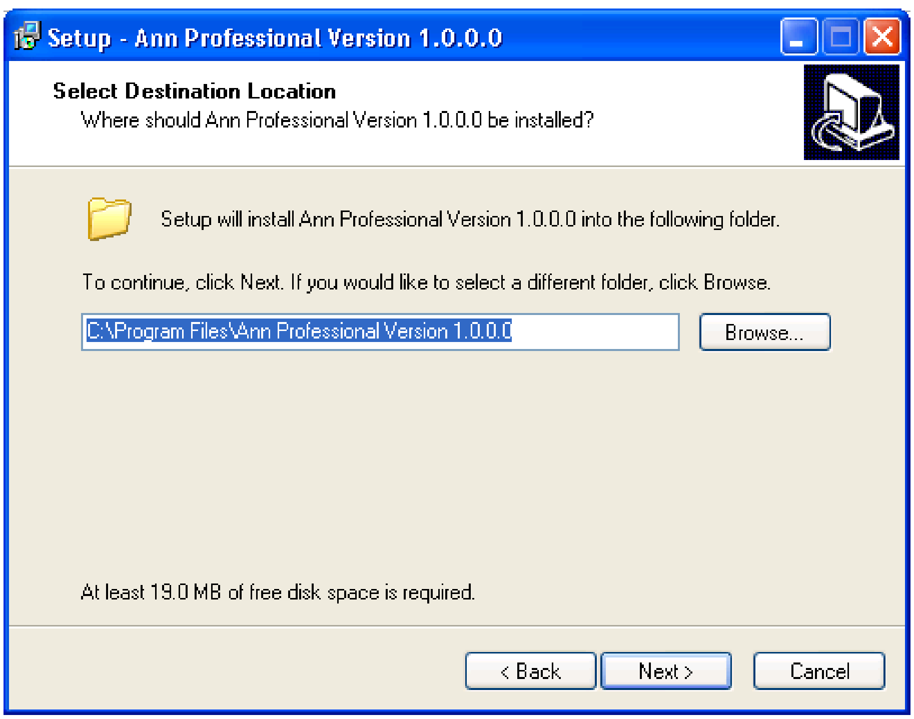


Figure 1-3. Selection of software installation directory.

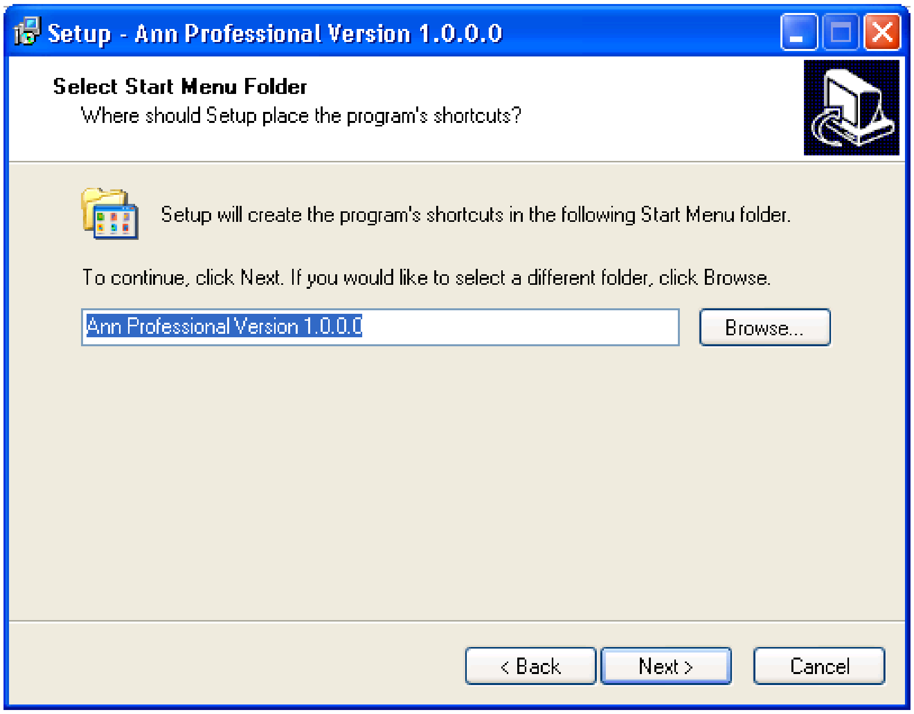


Figure 1-4. Creating shortcuts for ANN-Pro software.

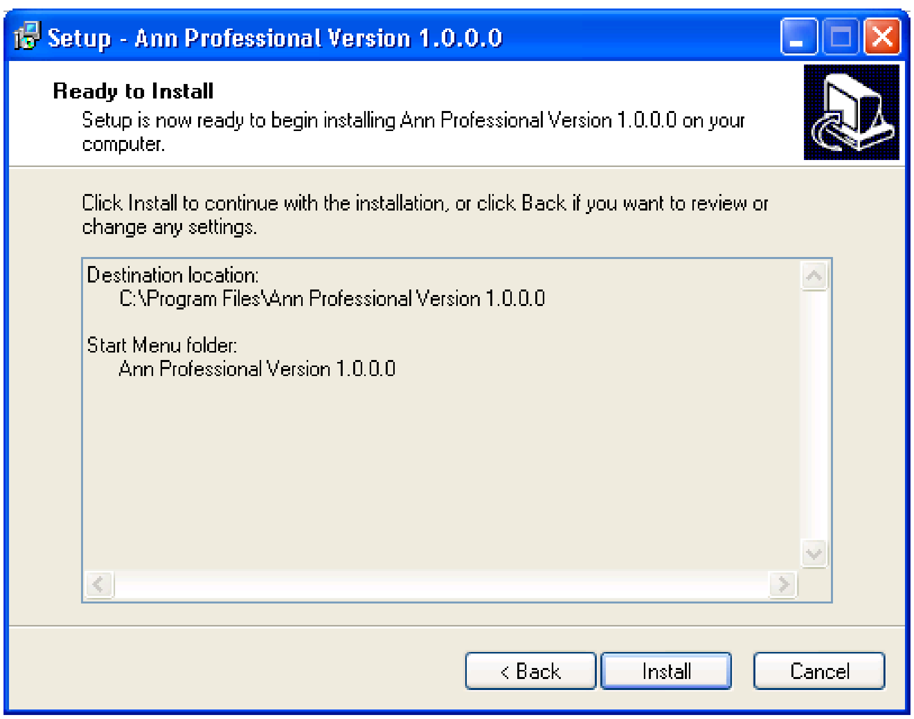


Figure 1-5. Verification screen for program setup and start menu folder.

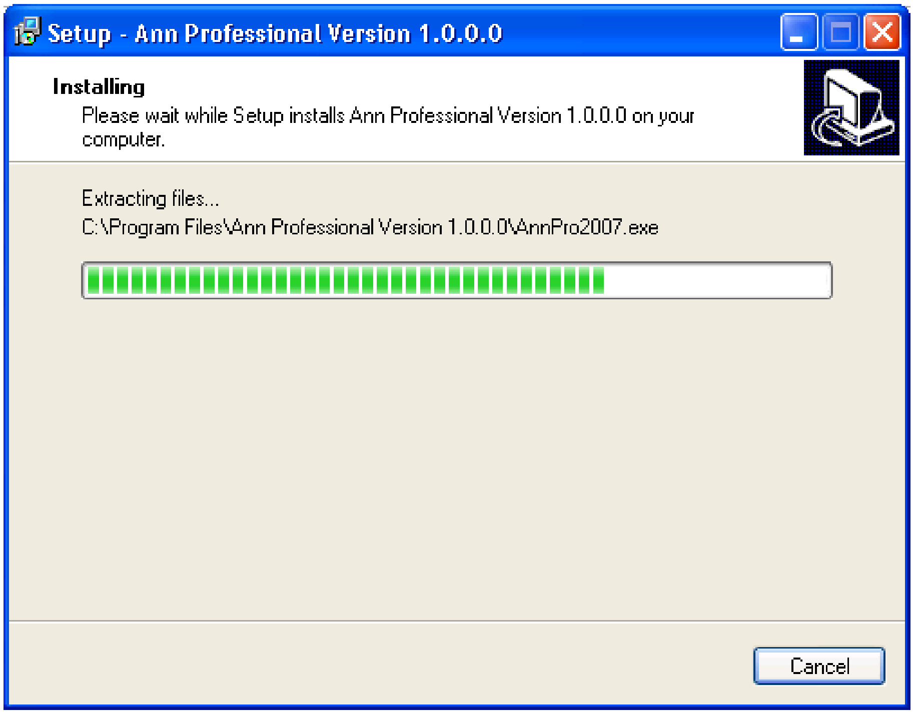


Figure 1-6. Monitoring of progress while the software is being set up.

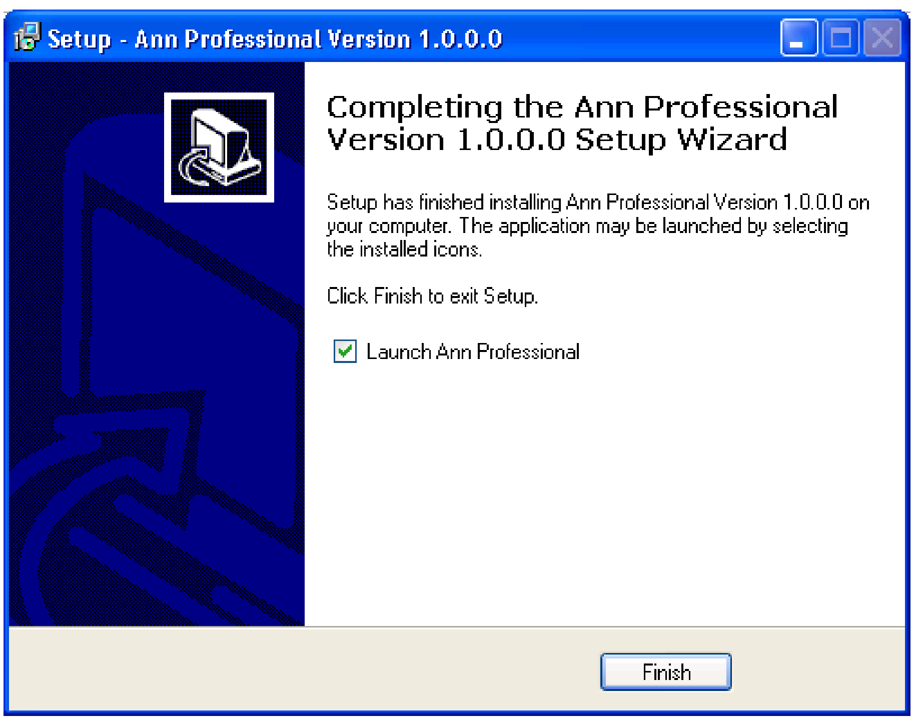


Figure 1-7. Completion of installation and agreement of software launch.

When the setup finishes successfully, ANN-Pro is launched with an introductory animation or movie (see Figure 1-8). It can be skipped by pressing the space button anytime. Then, the startup screen of the software is shown (see Figure 1-9). If any project was opened previously, then, the list of previous projects appears on the start-up screen (see Figure 1-10). These projects can be easily opened by just clicking on the interactive texts.

Figure 1-8. A snapshot from the introductory movie for ANN-Pro.

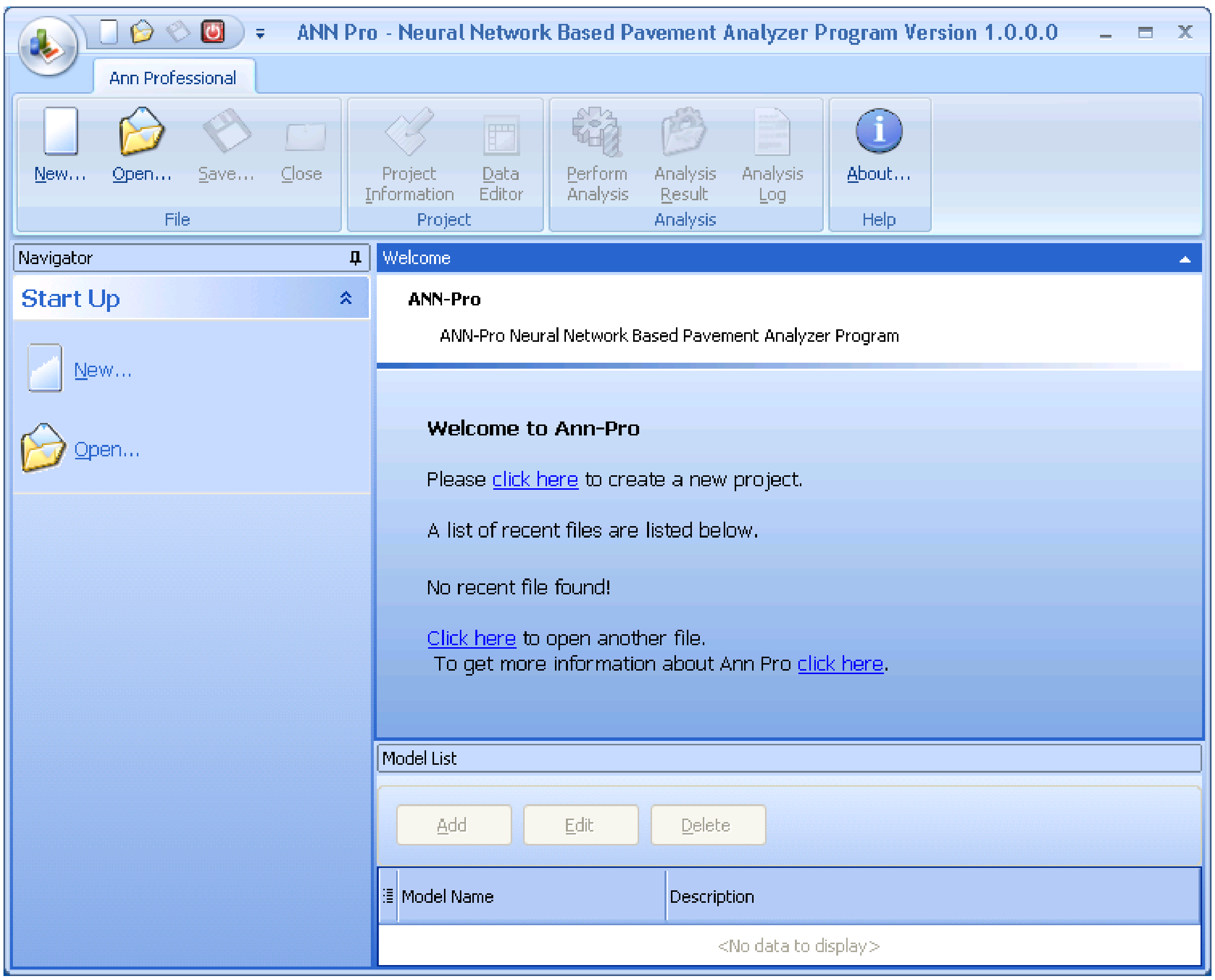


Figure 1-9. Startup screen of ANN-Pro.

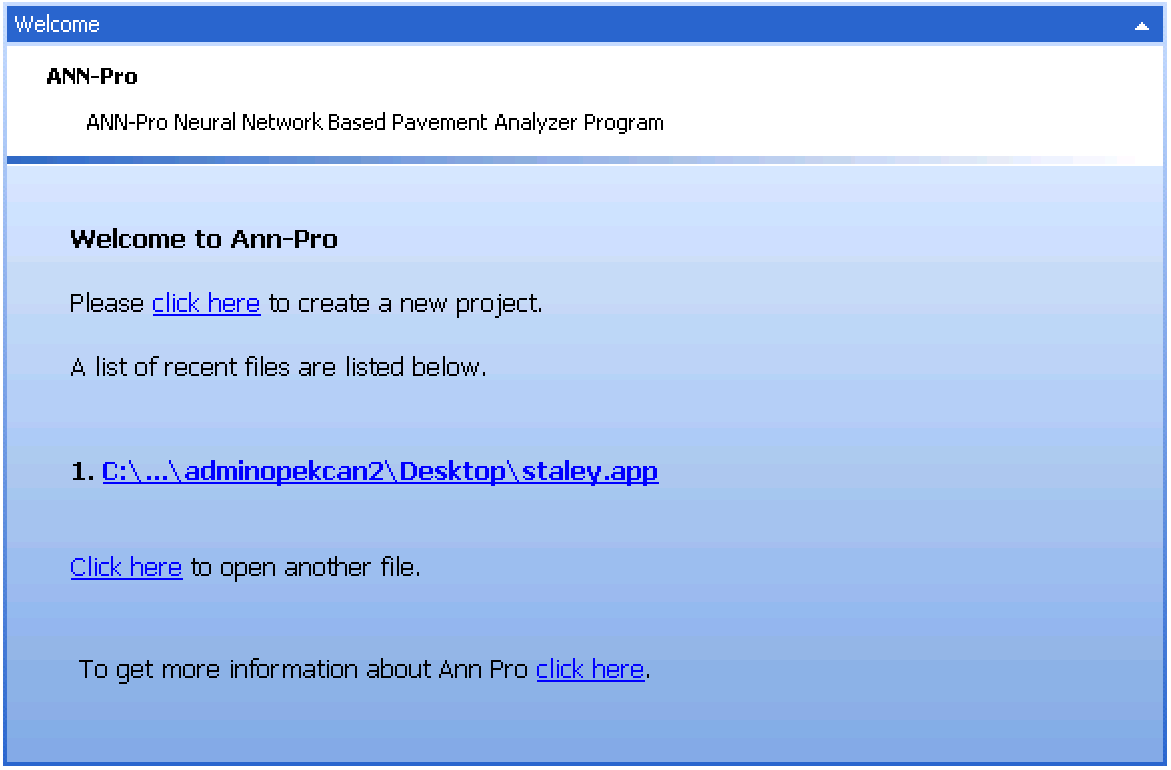


Figure 1-10. Welcome screen with a previously opened project.

CHAPTER 2: RUNNING FWD ANALYSES

In this chapter, pavement backcalculation analysis is performed using a sample FWD testing file. To illustrate the standard features, first, ANN structural models developed for backward and forward calculation are revisited. The details of these models can be found in the technical report. Then, a sample FWD file for Full Depth Asphalt Pavements is analyzed step by step to fully explain the capabilities of ANN-Pro. During this analysis, user friendly features of ANN-Pro are also explained for end users.

ANN STRUCTURAL MODELS

ANN-Pro contains many structural models developed for the forward and backward calculation of flexible pavement layer properties. Tables 2-1 to 2-4 provide the inputs and outputs of the current structural models implemented in the software. These models also have version numbers to enable updating based on ongoing and future research findings and the updated models will be included in the newer versions of this manual. Table 2-5 shows the abbreviations used in the software. Finally, Table 2-6 shows the current versions of the models available with ANN-Pro.

Table 2-1. Artificial Neural Network Models for Full Depth Asphalt Pavements

Name	Input	Output
FW-1	t_{AC},E_{AC}, E_{RI}	D_0, D_{12}, D_{24}, D_{36},ε_{AC}, ε_{SG},σ_D
BW-1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}	E_{AC}, E_{RI}
BW-2	D_0, D_{12}, D_{24}, D_{36}, t_{AC}	ε_{AC}, ε_{SG},σ_{DEV}

Table 2-2. Artificial Neural Network Models for Conventional Flexible Pavements

Name	Input	Output
FW-1	t_{AC}, t_{GB}, E_{AC}, K_{GB}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}, ε_{AC}, $\varepsilon_{SG,}\sigma_{DEV}$
BW-1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{GB}	E_{AC}, E_{RI}
BW-2	D_0, D_{12},D_{24}, D_{36}, t_{AC}, t_{GB}, E_{AC}, E_{RI}	K_{GB}
BW-3	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{GB}	ε_{AC}, $\varepsilon_{SG,}\sigma_{DEV}$

Table 2-3. Artificial Neural Network Models for Full Depth Asphalt Pavements on Lime Stabilized Soils

Name	Input	Output
FW-1	t_{AC}, t_{LSS}, E_{AC}, E_{LSS}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}
FW-2	t_{AC}, t_{LSS}, E_{AC}, E_{LSS}, E_{RI}	ε_{AC}, ε_{SG}, σ_{DEV}
BW-1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{LSS}	E_{AC}, E_{RI}
BW-2	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{LSS}, E_{AC}, E_{RI}	E_{LSS}
BW-3	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{LSS}	ε_{AC}, ε_{SG}, σ_{DEV}

Table 2-4. Artificial Neural Network Models for Conventional Flexible Pavements on Lime Stabilized Soils

Name	Input	Output
FW-1	t_{AC}, t_{GB}, t_{LSS}, E_{AC}, K_{GB}, E_{LSS}, E_{RI}	D_0, D_{12}, D_{24}, D_{36}
FW-2	t_{AC}, t_{GB}, t_{LSS}, E_{AC}, K_{GB}, E_{LSS}, E_{RI}	ε_{AC}, ε_{SG}, σ_{DEV}
BW-1	D_0, D_{12}, D_{24}, D_{36}, t_{AC}, t_{GB}, t_{LSS}	E_{AC}, E_{RI}

All structural models developed for full depth asphalt pavements (FDP), conventional flexible pavements (CFP), full depth asphalt pavements on lime stabilized soils (FDP-LSS) were validated with field data. However, conventional flexible pavements on lime stabilized soils (CFP-LSS) could not be validated since field FWD data were not available. Therefore, the reliability of CFP-LSS structural models cannot be assured fully. However, their validation with synthetic data obtained from the ILLI-PAVE FE program was accomplished successfully.

Table 2-5. List of abbreviations used in the ANN-Pro

FDP	Full-depth asphalt pavement
FDP-LSS	Full-depth asphalt pavement on lime stabilized subgrade
CFP	Conventional flexible pavement
CFP-LSS	Conventional flexible pavement on lime stabilized subgrade
D_i	Sensor deflection corresponding to 9000 lb loading at a distance of “i” inches from the center of loading (in mils)
t_{AC}	Thickness of asphalt concrete layer in inches
t_{LSS}	Thickness of lime stabilized soil layer in inches
t_{GB}	Thickness of granular base layer in inches
E_{AC}	Elastic layer modulus of asphalt concrete layer in psi
E_{LSS}	Elastic layer modulus of lime stabilized soil layer in psi
K_{GB}	modulus constant for stress-dependent granular base K-θ model in psi
E_{Ri}	Breakpoint resilient modulus of unmodified subgrade in psi
ε_{AC}	Horizontal strain at the bottom of asphalt concrete layer in inch/inch
ε_{SG}	Vertical strain on top of the subgrade in inch/inch
σ_{DEV}	Deviator stress on top of subgrade in psi

Table 2-6. ANN Structural Models Available for ANN-Pro Version 1.0.0.0

Software Version	v 1.0.0.0	
First Release Date	July 11, 2007	
Available Models		
Pavement Type	Model Name	Model Version (m)
FDP	FW-1	1.0.0
	BW-1	1.0.0
	BW-1	1.0.0
CFP	FW-1	1.0.0
	BW-1	1.0.0
	BW-2	1.0.0
	BW-3	1.0.0
FDP-LSS	FW-1	1.0.0
	FW-2	1.0.0
	BW-1	1.0.0
	BW-2	1.0.0
	BW-3	1.0.0
CFP-LSS	FW-1	1.0.0
	FW-2	1.0.0
	BW-1	1.0.0

SOFTWARE COMPONENTS

ANN-Pro contains toolbars that are designed to make the users better organized and comfortable while performing FWD backcalculation analysis. These are Standard Toolbar, Navigator Toolbar, Data Editor Toolbar and Results Toolbar. These toolbars are mainly used to manage all operations in the software including file management, running neural network analysis and viewing results in a user-friendly environment. The task of each button in a toolbar is self-explanatory; however, they will be explained in detail using figure titles while running a sample FWD analysis.

Standard toolbar (see Figure 2-1) is mainly used to reproduce file processing functions using shortcuts. These are for creating a new file (New), opening an existing file (Open), saving a project file (Save) and closing a currently open file (Close). Instant access to project information and data editor is possible. In addition, FWD analysis can be performed (Perform Analysis) and the results including the analysis log are viewed easily at any time (Analysis Result and Analysis Log). Finally, the latest version number can be viewed using standard toolbar (About) (see Figure 2-2).

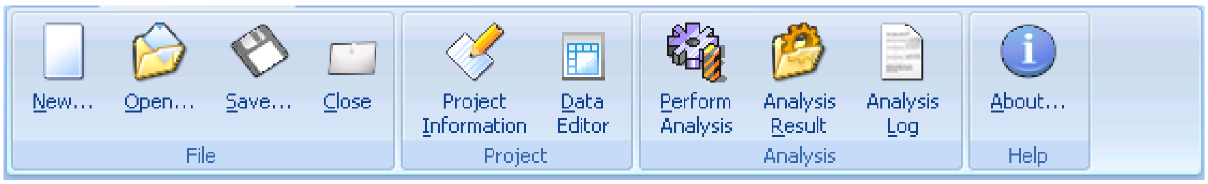


Figure 2-1. Standard toolbar.

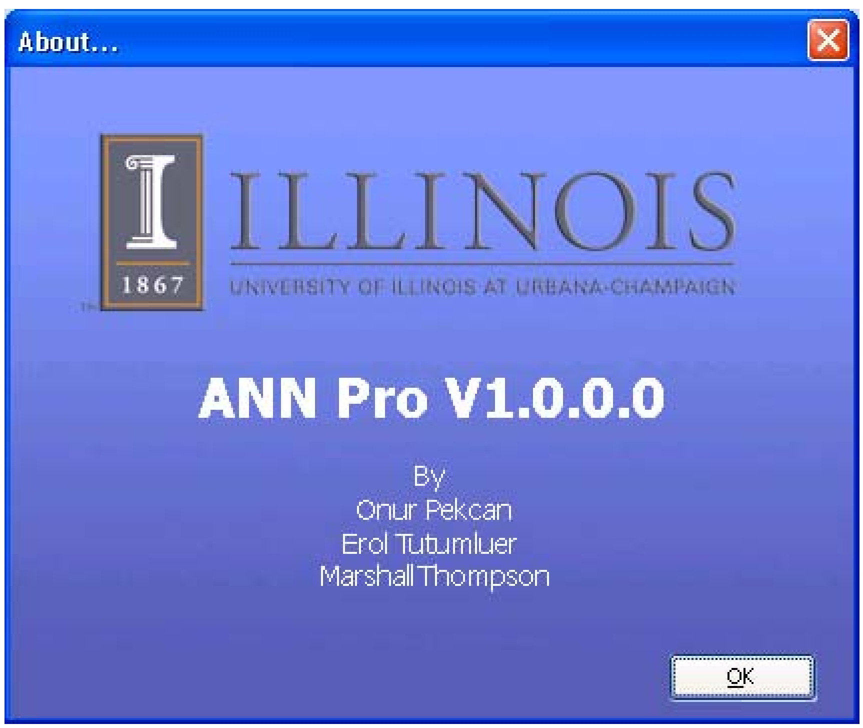


Figure 2-2. Version information through about button.

Navigator toolbar (see Figure 2-3) is mainly used to direct the user in running FWD analysis step by step. The first step is to enter project information (Project Information). The second step is to import the FWD data from a file into the program (Data Editor). Then, the FWD analysis needs to be run using "Perform Analysis" button. After a successful FWD run, the results can be viewed using "Analysis Result" and "Analysis Log" buttons.

In all Windows based programs, the shortcuts are replicated in different places of the software. Similarly, in ANN-Pro, there are many buttons such as Analysis Results, Perform

Analysis, etc. available redundantly. In fact, the navigator toolbar is fully embedded in the Standard Toolbar. This way, the user will have the flexibility to use these buttons.

Data editor toolbar (see Figure 2-4) is the most comprehensive and capable toolbar since FWD data needs to be modified before importing it to ANN-Pro. It includes many buttons that are designed to quickly import and export data. Import Data button provides regular and special import options while Export Data button easily exports data to Microsoft Excel. Copy button is used for copying the whole column or row in ANN-Pro data editor. Paste button is used to paste the data into ANN-Pro editor. Set Selection Value button is

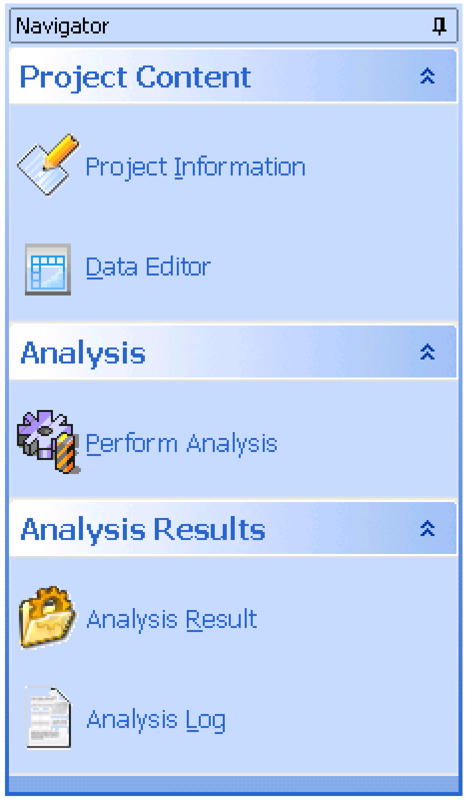


Figure 2-3. Navigator toolbar.

used for column or row operations such as entering values of layer thicknesses for the whole row or column, etc. Analysis Selected button is used to run FWD analysis for selected rows. In addition to these, adding, inserting or deleting rows are possible in the program. Clear button clears the whole data in the data editor. Custom Columns is used to create columns based on user's request. Finally, Script Editor is ANN-Pro's own script editor that may be used to program ANN-Pro data.

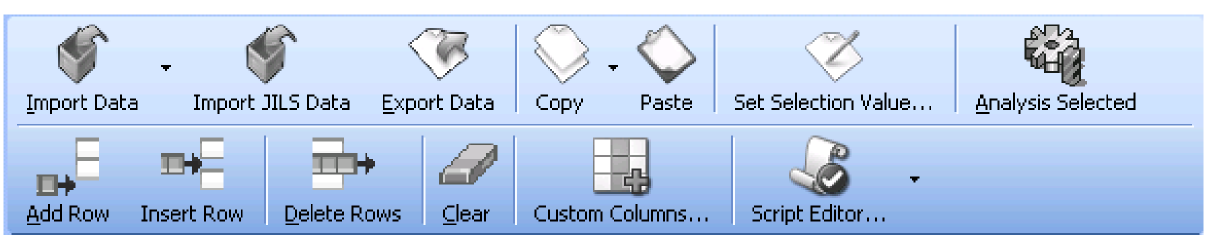


Figure 2-4. Data editor toolbar.

Results toolbar (Figure 2-5) is used for viewing results in a user friendly environment. Graph button is used to plot analysis results. The results can be exported in “xls”, “xml”, “csv” and “html” file format while the graphs can be exported in “bmp” format (Export button). In addition, the results can directly be exported to any spreadsheet program using Copy button in the results toolbar. Finally, View Button can be used to view the data in different ways such as showing only data statistics, data inputs or summary etc.

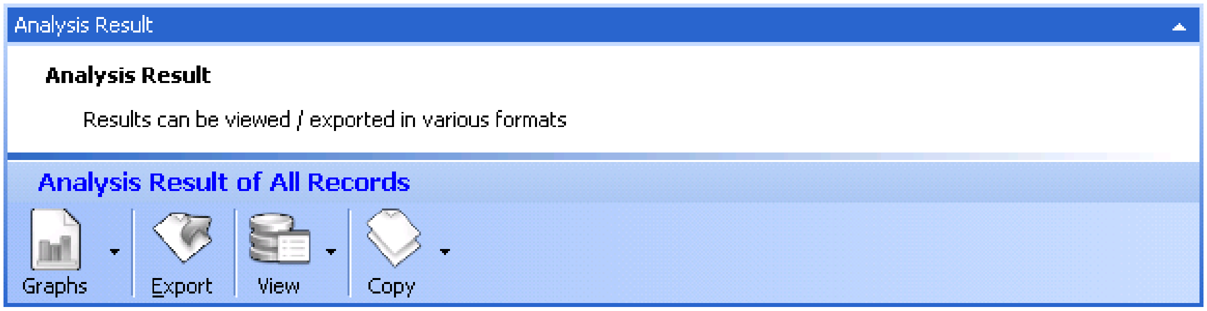
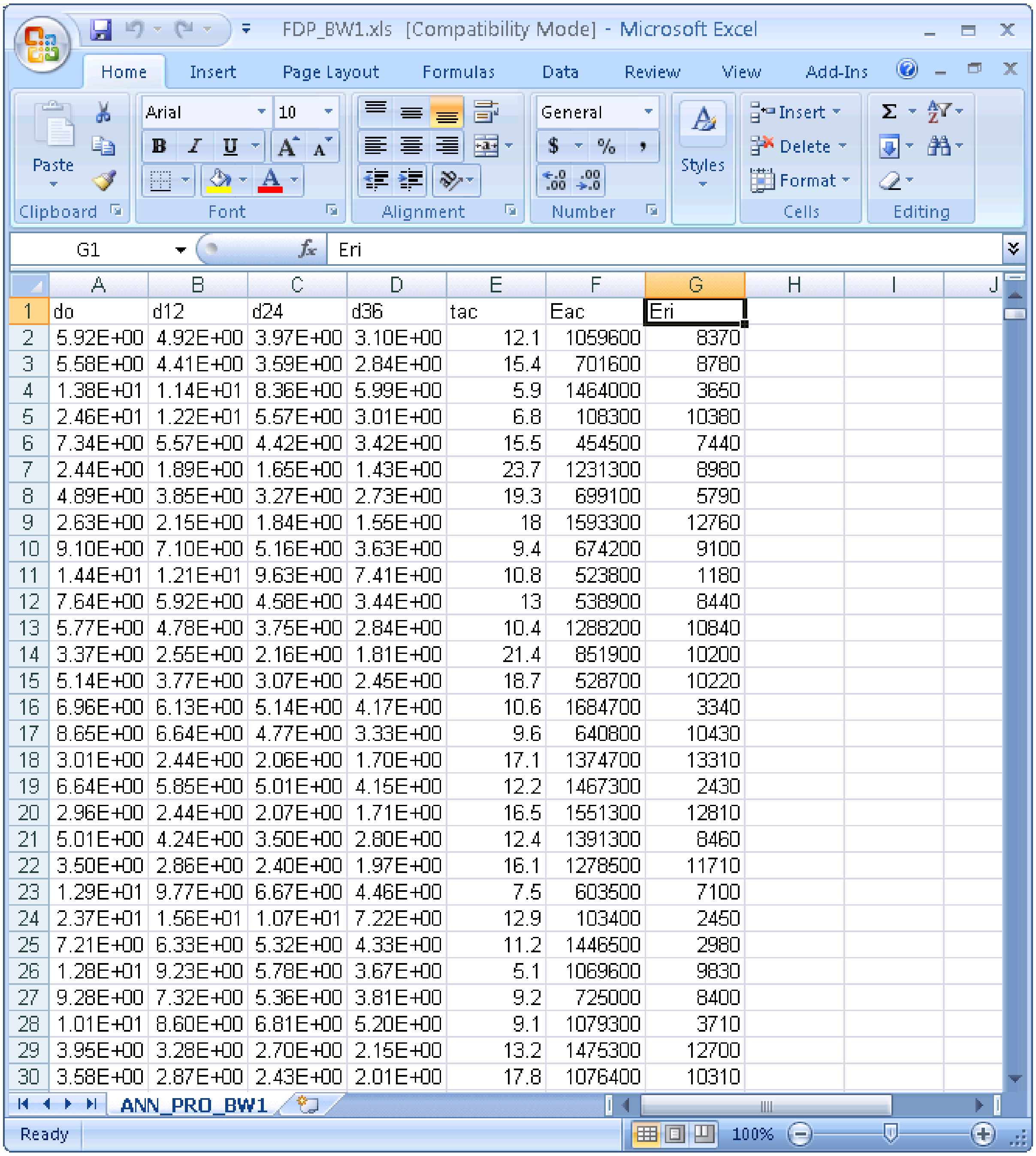


Figure 2-5. Results toolbar.

RUNNING A SAMPLE FWD ANALYSIS (QUICK START)

In this section, an example problem is solved to backcalculate flexible pavement layer properties. Sample data obtained using ILLI-PAVE finite element analysis program are used to test the capabilities of the neural network based structural model. One hundred FWD stations are randomly selected from the database which was used to test BW-1 model developed for full depth asphalt pavements. The FWD data including thickness information are stored in Microsoft Excel together with ILLI-PAVE estimates of layer properties (see Figure 2-6). Figures 2-7 through 2-26 illustrate the steps necessary to run the analysis for the above mentioned data.

1. Click on Start button and select ANN-Pro from Programs Menu (Figure 2-7).
2. First an introductory movie appears and then ANN-Pro starts (Figure 2-8).
3. Click on New button to create an empty project and select Empty Project to save the results of FWD analysis (Figure 2-9).
4. Complete the project information form (Figure 2-10).
5. Click on Add Model button (Figure 2-8) on Model List toolbar to select ANN structural model for backward analysis. The corresponding pavement model needs to be specified along with the ANN structural model (Figure 2-11). The whole screen should be viewed to confirm the selected model (Figure 2-12).
6. Select Data Editor using Navigation Toolbar to import FWD data and examine the required input format of the structural model (Figure 2-13).
7. Click on Import Data once to import the FWD data from MS Excel and show the location of Excel file in the computer and click Next (Figure 2-14).
8. Select the sheet where the data are available (Figure 2-15).
9. Define the copy/paste area in the sheet using Excel column and row numbers and click Next (Figure 2-16). Deflections are normalized to 9 000 lb load prior to importing.
10. Make sure the data are imported correctly by examining the rows and columns in the data editor (Figure 2-17). Enter thickness values if necessary.
11. Click on Perform Analysis button in the navigation toolbar to run ANN analysis, the details of which are shown on the screen (Figure 2-18).
12. After ANN analysis is finished successfully (it usually takes 2 to 15 seconds depending on the number of data and processor speed of the computer), the results are automatically given by ANN-Pro (Figure 2-19).
13. The inputs and outputs are automatically shown on the data editor by default. However, users can modify the appearance of results by specifying different views in View Button (Figure 2-20). For example, users can view their estimates and ANN results together by selecting user outputs, i.e., estimates (Figure 2-21). ANN outputs, however, are always shown on the data editor.
14. The users can view the data statistics by clicking on Show Statistics (Figure 2-22).
15. The results can also be shown using two-way graphs (generally, x axis shows the user estimates, y axis shows the results of ANN analysis). To plot a two-way graph, Graph button needs to be clicked once (Figure 2-23).
16. After pressing Add Graph button, the graph wizard is shown (Figure 2-24). Users can select any two columns that are already shown on the results screen. Showing legends, background images and drawing “y=x” line are given as options to users. Selection of these options needs to be confirmed.
17. A sample plot is shown in Figure 2-25. This can be exported using Export button in “bmp” file format (Figure 2-26). Alternatively, results can be copied into Excel and graphs can be created using this program.



do	d12	d24	d36	tac	Eac	Eri
5.92E+00	4.92E+00	3.97E+00	3.10E+00	12.1	1059600	8370
5.58E+00	4.41E+00	3.59E+00	2.84E+00	15.4	701600	8780
1.38E+01	1.14E+01	8.36E+00	5.99E+00	5.9	1464000	3650
2.46E+01	1.22E+01	5.57E+00	3.01E+00	6.8	108300	10380
7.34E+00	5.57E+00	4.42E+00	3.42E+00	15.5	454500	7440
2.44E+00	1.89E+00	1.65E+00	1.43E+00	23.7	1231300	8980
4.89E+00	3.85E+00	3.27E+00	2.73E+00	19.3	699100	5790
2.63E+00	2.15E+00	1.84E+00	1.55E+00	18	1593300	12760
9.10E+00	7.10E+00	5.16E+00	3.63E+00	9.4	674200	9100
1.44E+01	1.21E+01	9.63E+00	7.41E+00	10.8	523800	1180
7.64E+00	5.92E+00	4.58E+00	3.44E+00	13	538900	8440
5.77E+00	4.78E+00	3.75E+00	2.84E+00	10.4	1288200	10840
3.37E+00	2.55E+00	2.16E+00	1.81E+00	21.4	851900	10200
5.14E+00	3.77E+00	3.07E+00	2.45E+00	18.7	528700	10220
6.96E+00	6.13E+00	5.14E+00	4.17E+00	10.6	1684700	3340
8.65E+00	6.64E+00	4.77E+00	3.33E+00	9.6	640800	10430
3.01E+00	2.44E+00	2.06E+00	1.70E+00	17.1	1374700	13310
6.64E+00	5.85E+00	5.01E+00	4.15E+00	12.2	1467300	2430
2.96E+00	2.44E+00	2.07E+00	1.71E+00	16.5	1551300	12810
5.01E+00	4.24E+00	3.50E+00	2.80E+00	12.4	1391300	8460
3.50E+00	2.86E+00	2.40E+00	1.97E+00	16.1	1278500	11710
1.29E+01	9.77E+00	6.67E+00	4.46E+00	7.5	603500	7100
2.37E+01	1.56E+01	1.07E+01	7.22E+00	12.9	103400	2450
7.21E+00	6.33E+00	5.32E+00	4.33E+00	11.2	1446500	2980
1.28E+01	9.23E+00	5.78E+00	3.67E+00	5.1	1069600	9830
9.28E+00	7.32E+00	5.36E+00	3.81E+00	9.2	725000	8400
1.01E+01	8.60E+00	6.81E+00	5.20E+00	9.1	1079300	3710
3.95E+00	3.28E+00	2.70E+00	2.15E+00	13.2	1475300	12700
3.58E+00	2.87E+00	2.43E+00	2.01E+00	17.8	1076400	10310

Figure 2-6. Sample FWD file in Microsoft Excel.

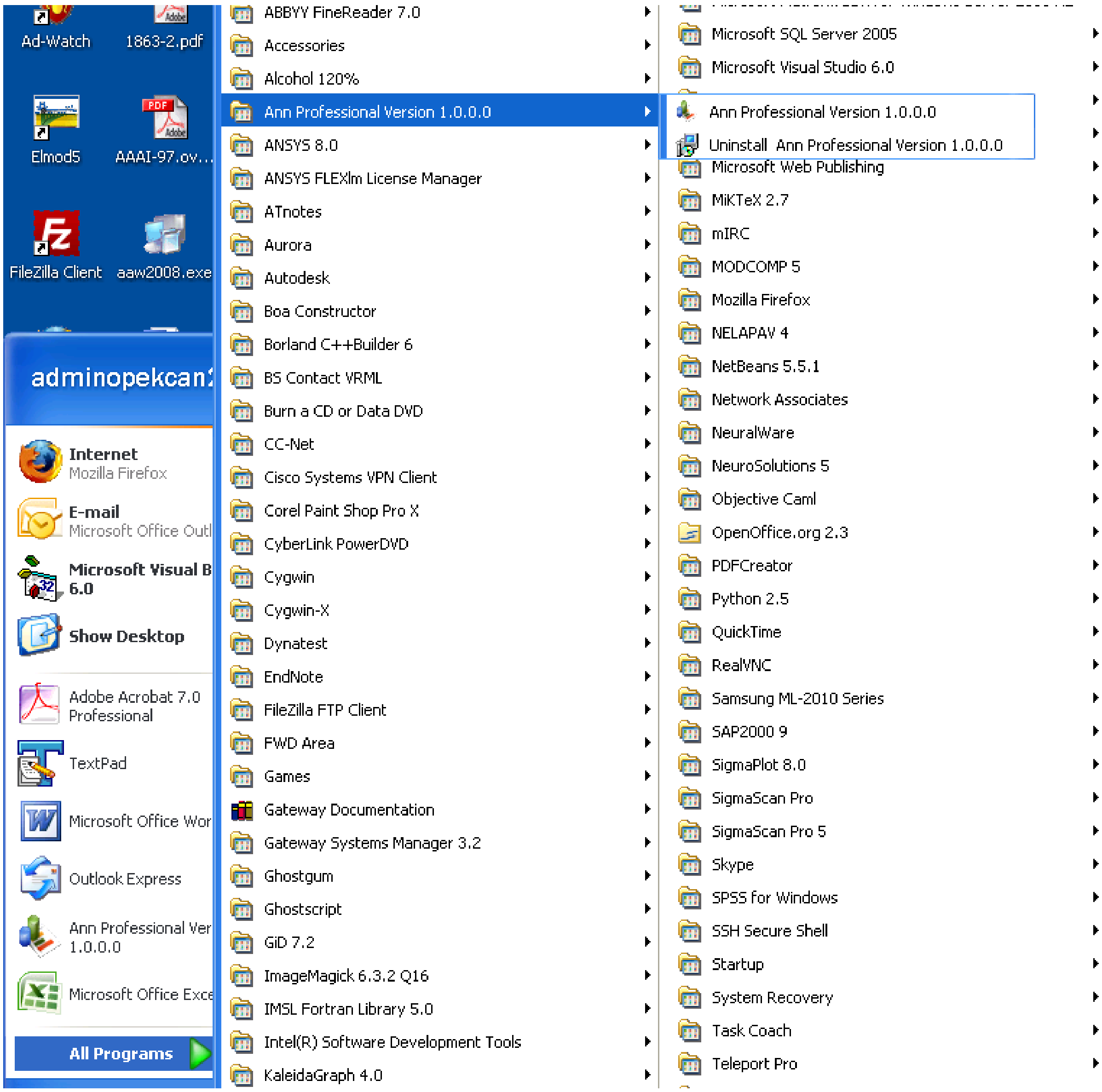


Figure 2-7. Running ANN-Pro using Windows programs.

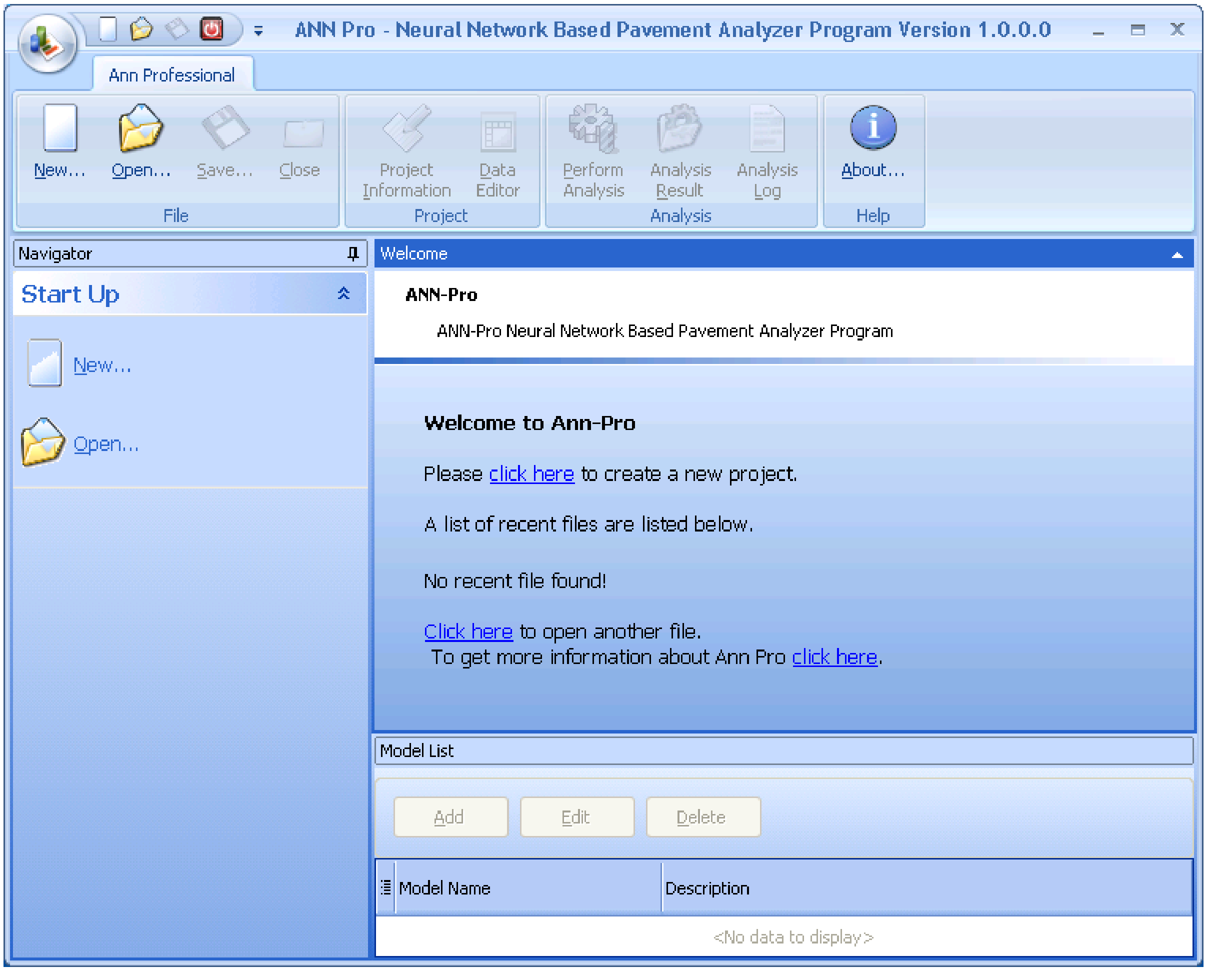


Figure 2-8. Start-up screen of ANN Pro.

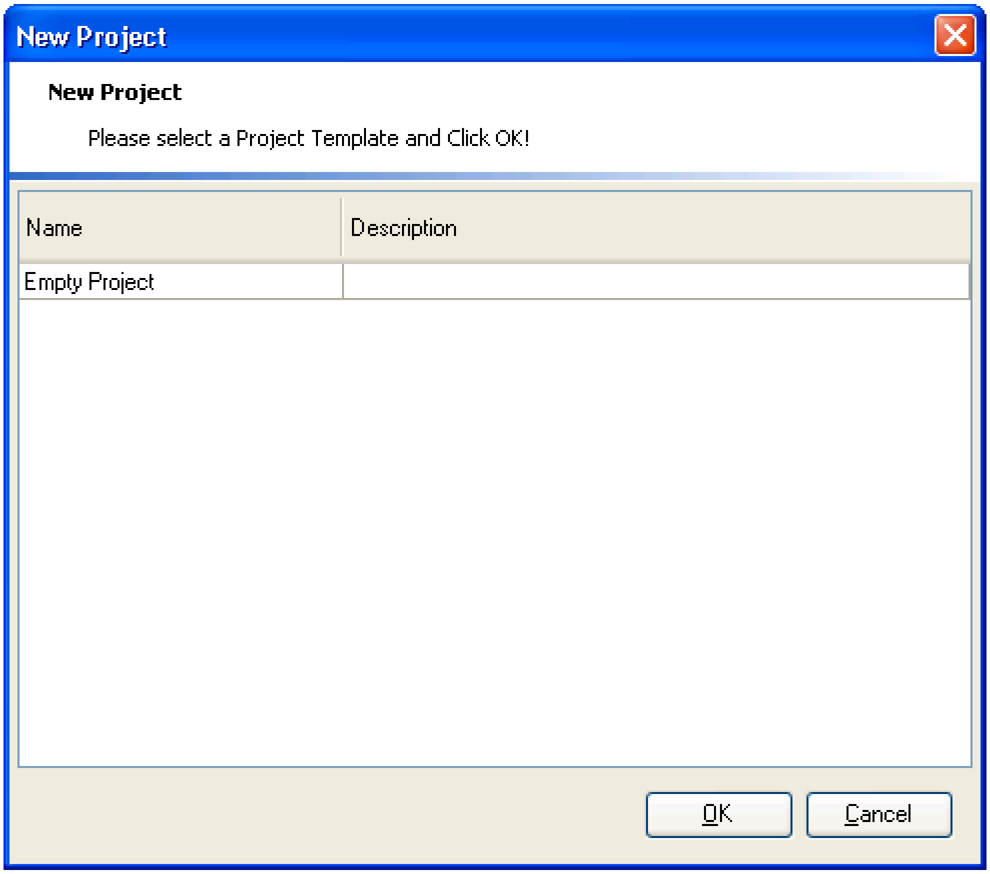


Figure 2-9. Selection of a project template to begin FWD analysis.

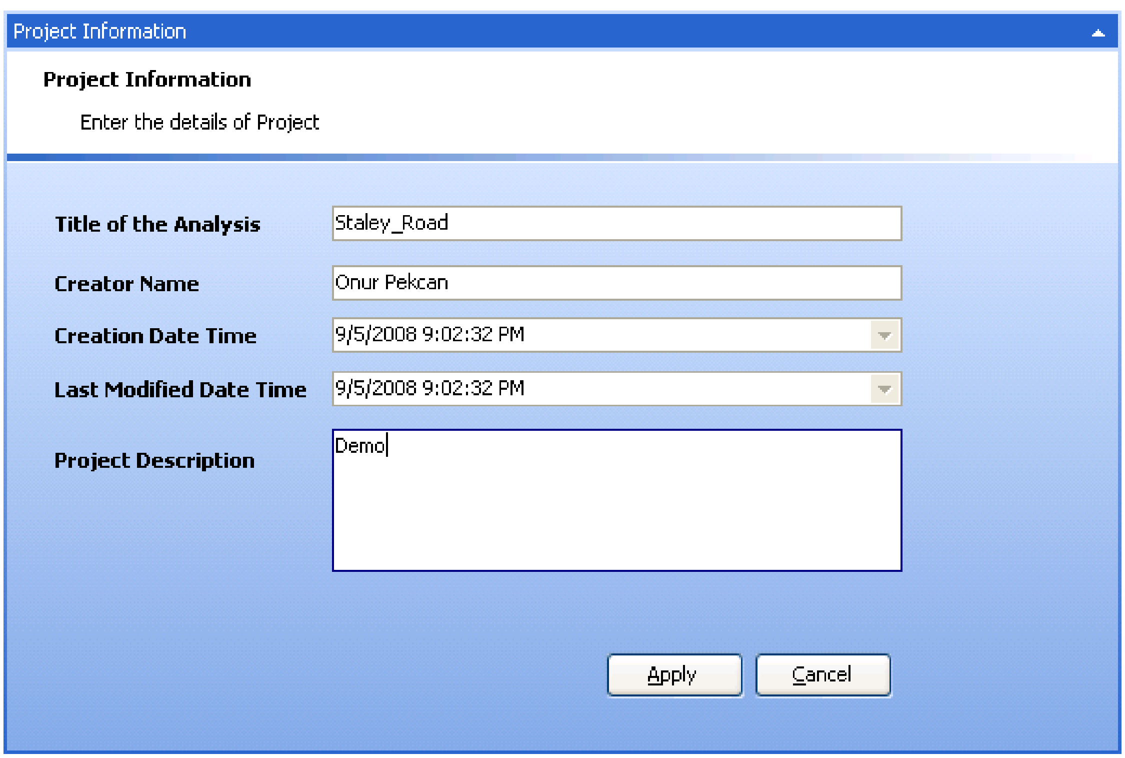


Figure 2-10. Project Information screen for entering analysis details.

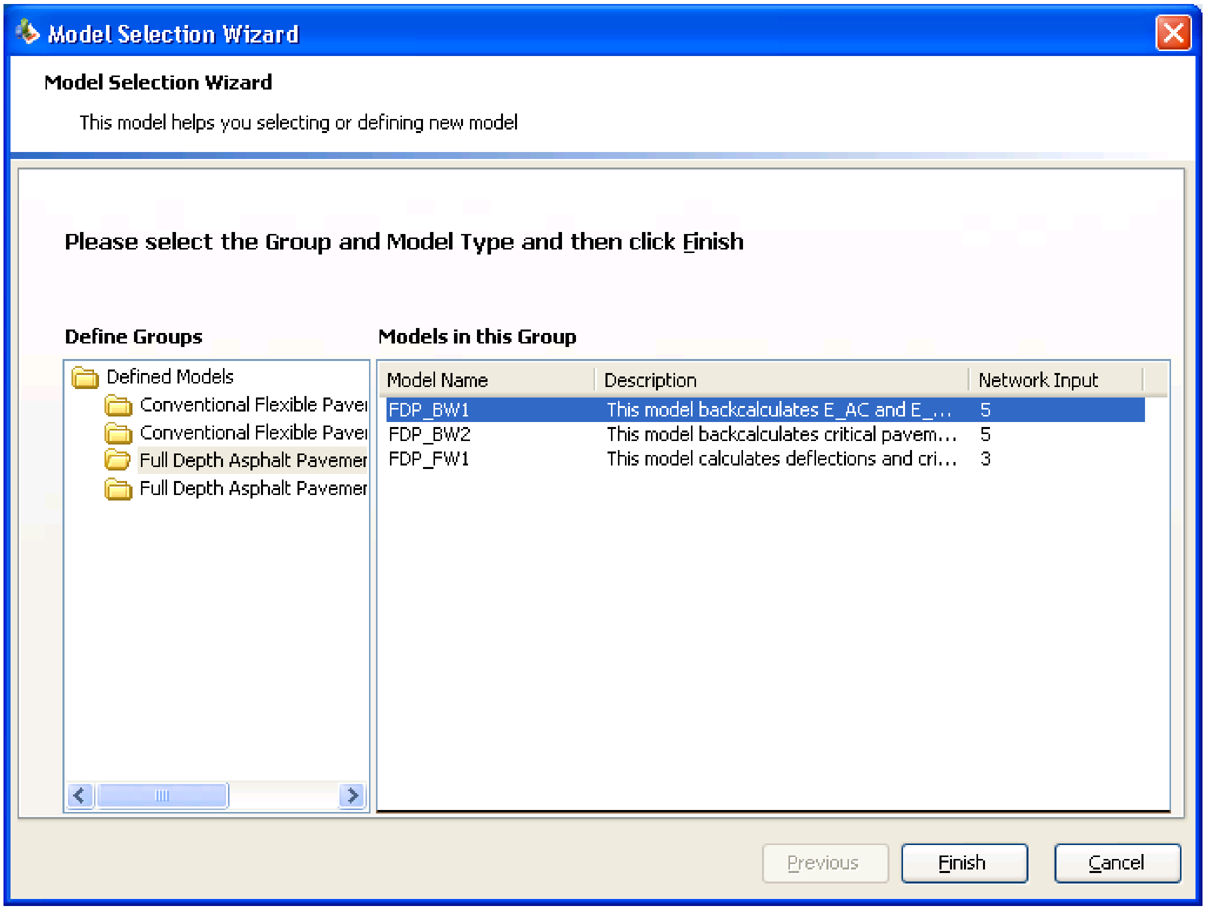


Figure 2-11. Model selection wizard for different flexible pavements.

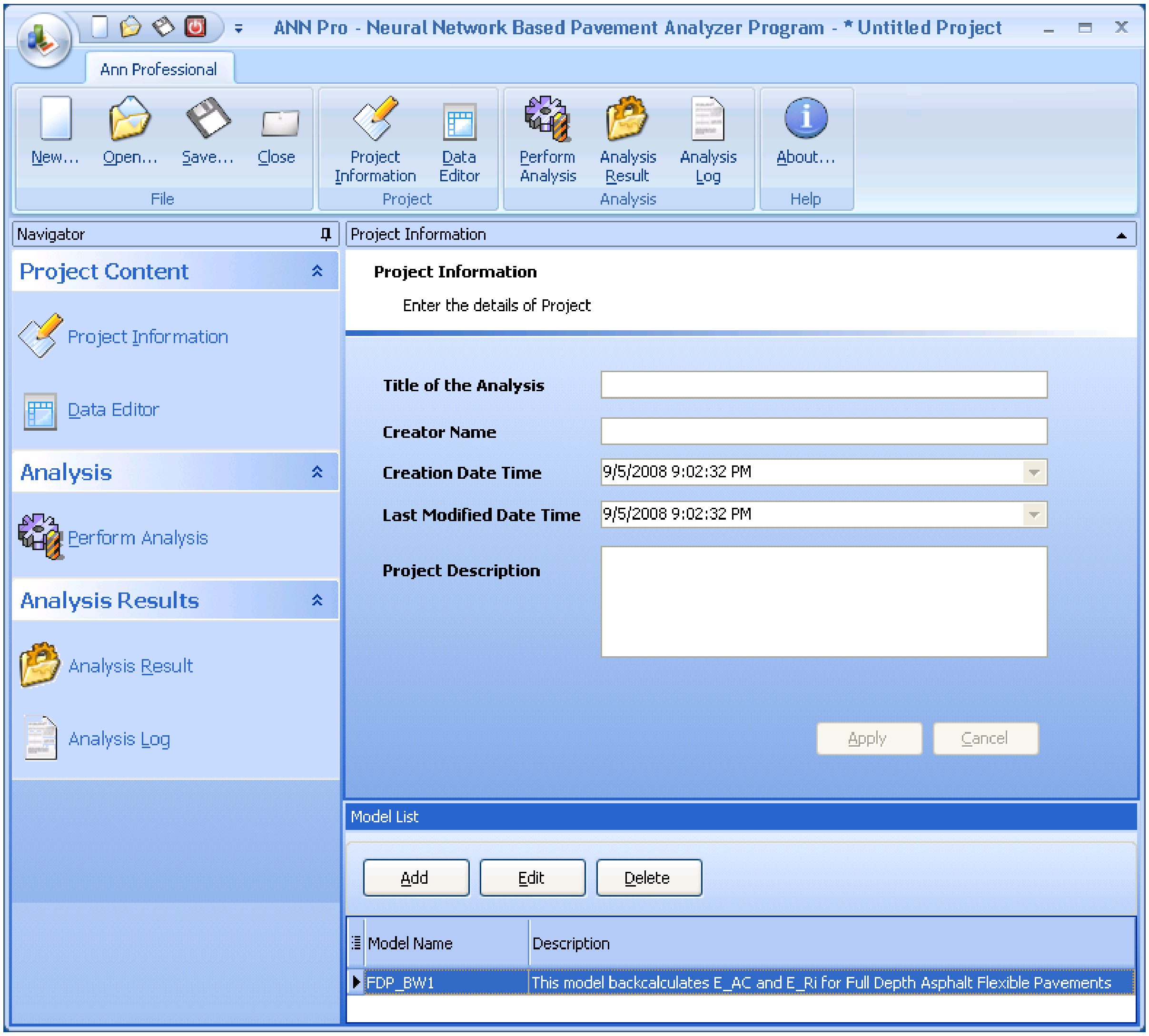


Figure 2-12. Overview of ANN-Pro together with selected model.

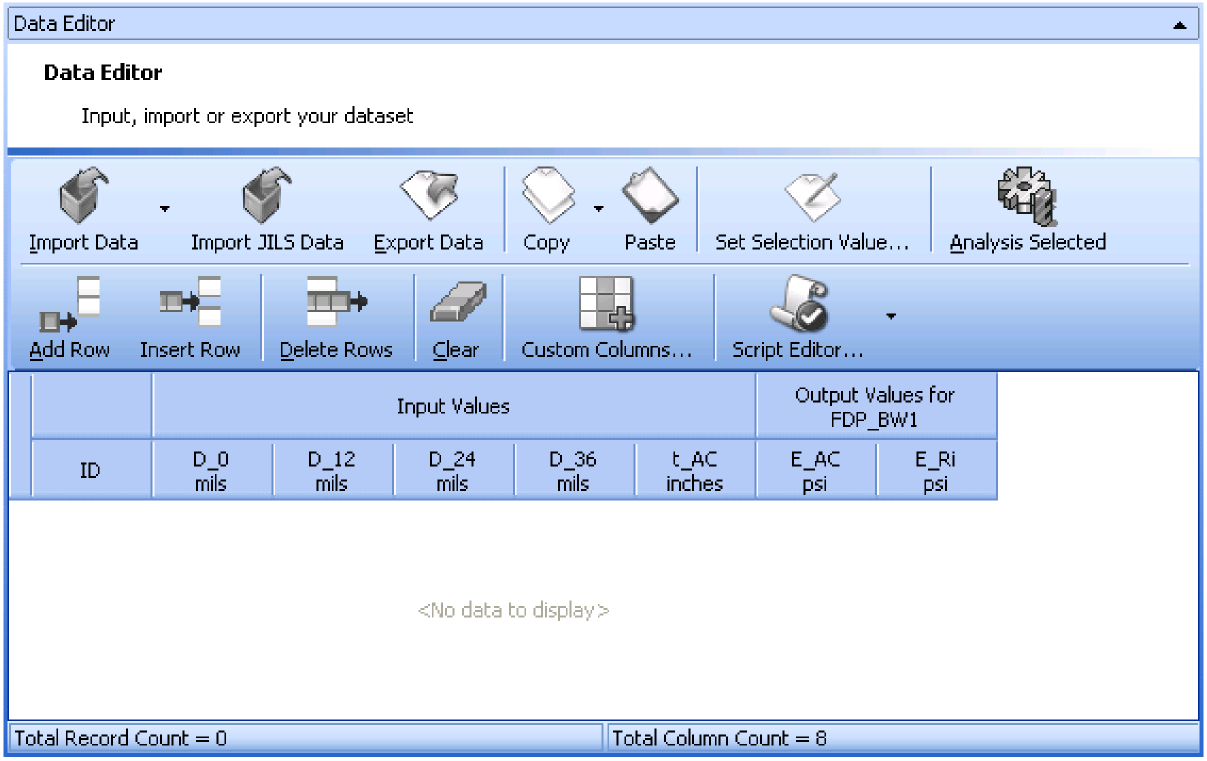


Figure 2-13. Data editor view of the selected model.

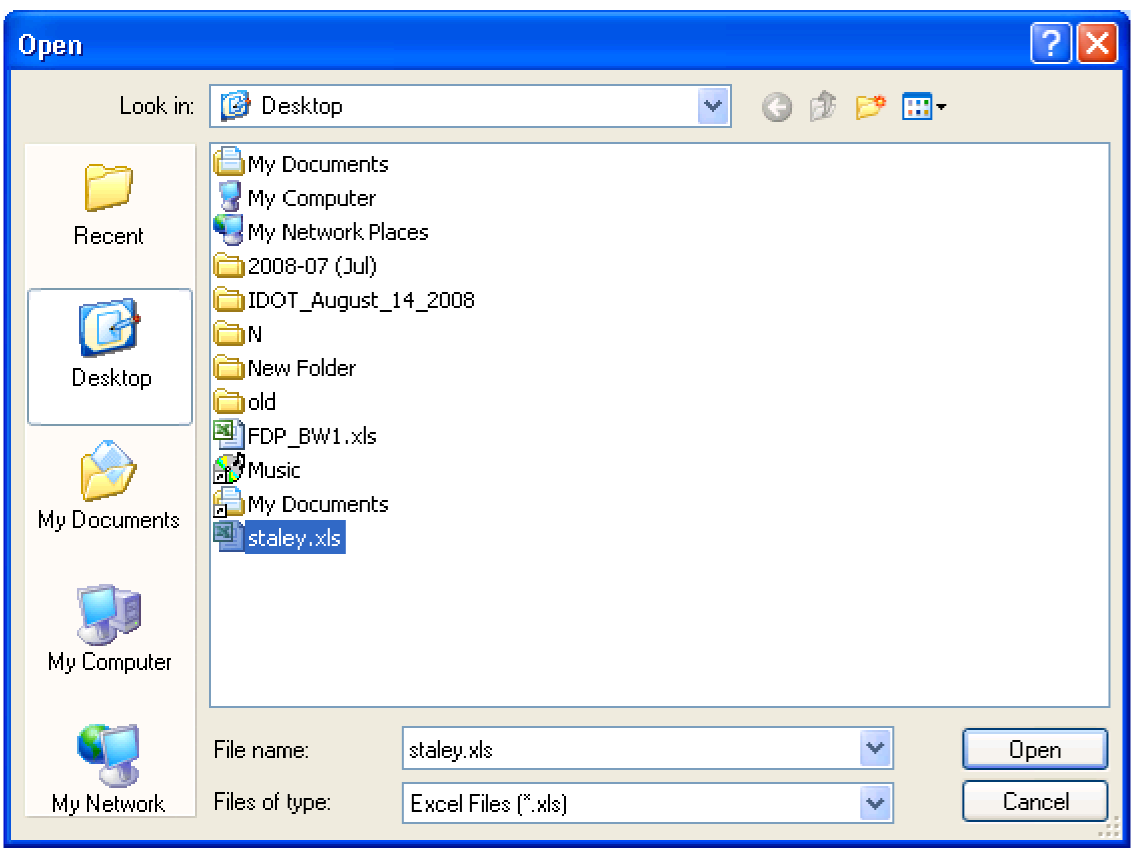


Figure 2-14. Microsoft Excel import wizard: selection of source file.

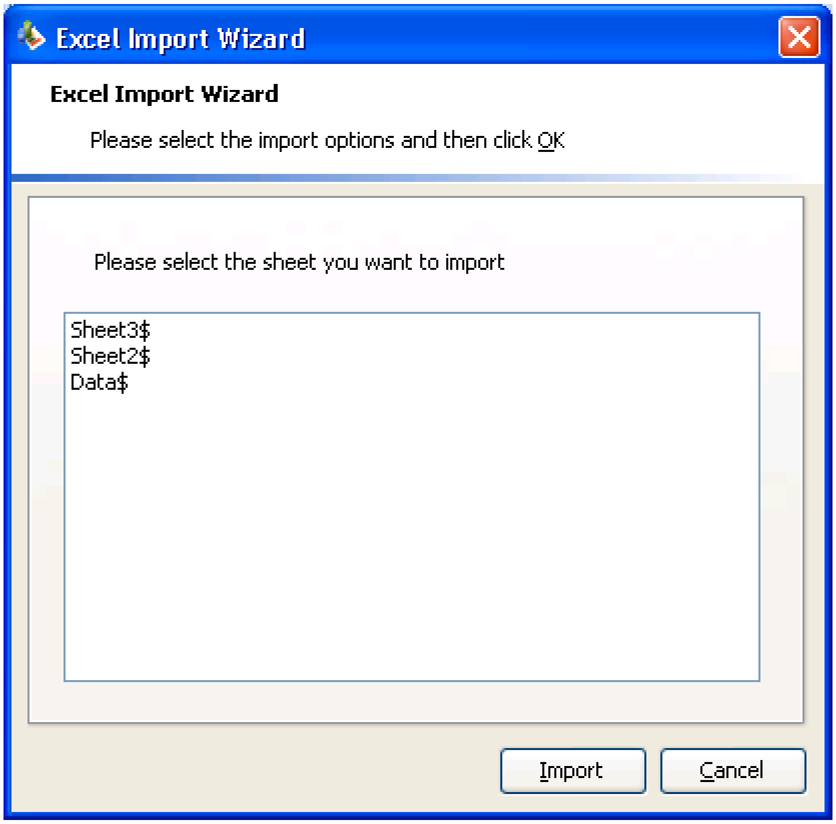


Figure 2-15. Microsoft Excel import wizard: selection of available sheets.

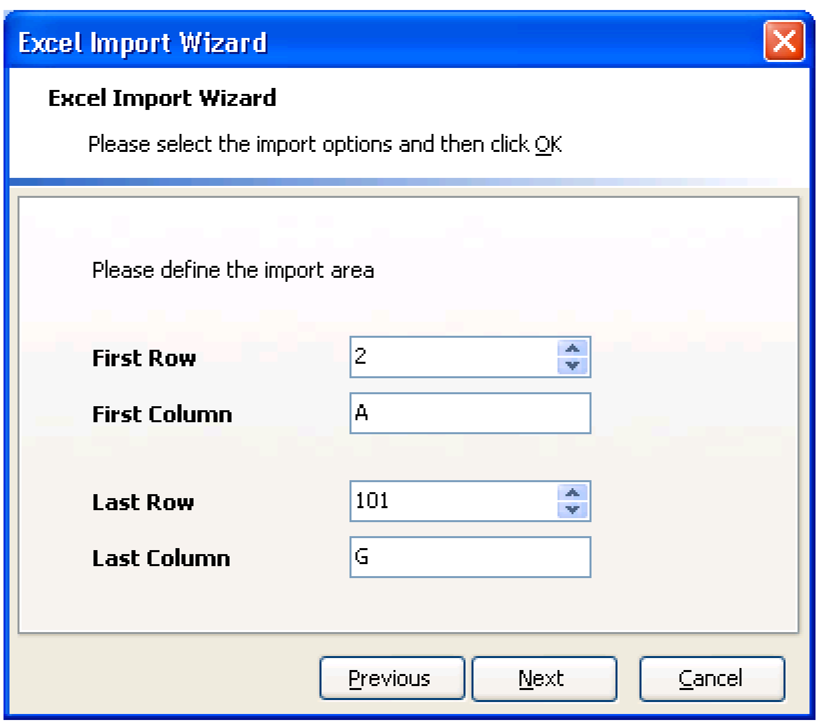
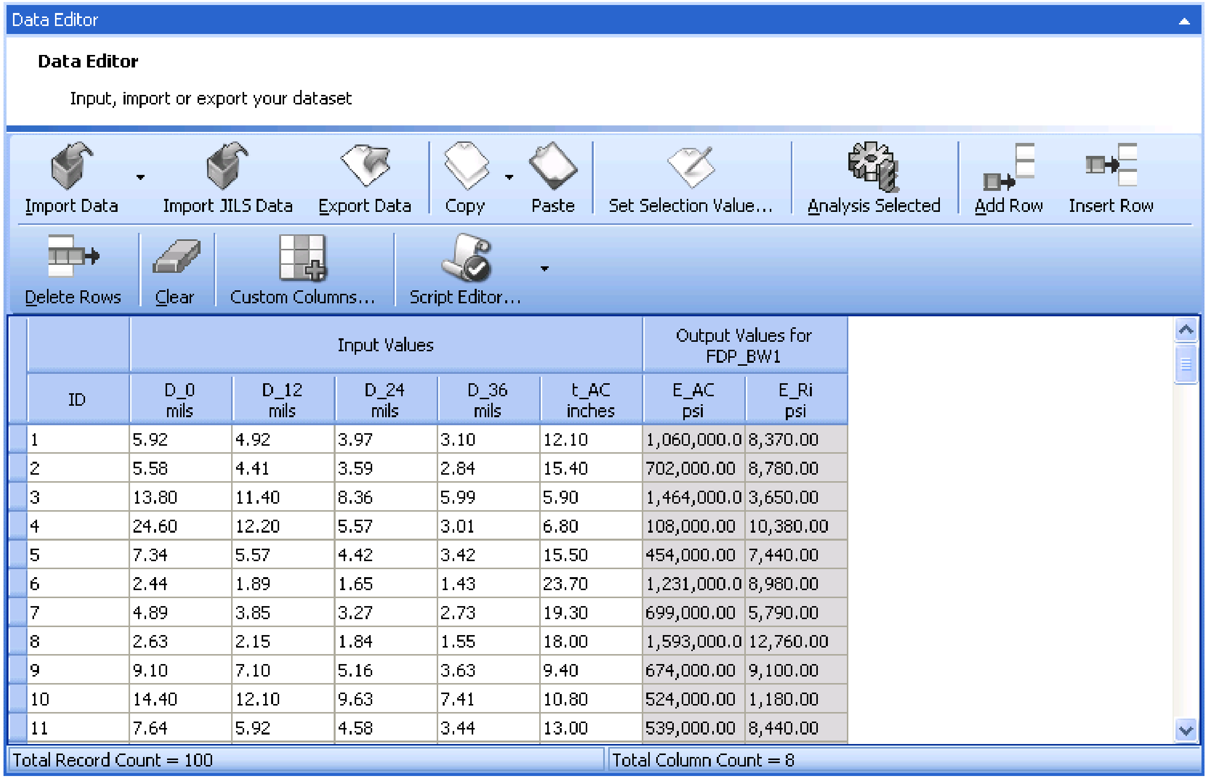


Figure 2-16. Microsoft Excel import wizard: defining import area in selected sheet.



	Input Values					Output Values for FDP_BW1	
ID	D_0 mils	D_12 mils	D_24 mils	D_36 mils	t_AC inches	E_AC psi	E_Ri psi
1	5.92	4.92	3.97	3.10	12.10	1,060,000.0	8,370.00
2	5.58	4.41	3.59	2.84	15.40	702,000.00	8,780.00
3	13.80	11.40	8.36	5.99	5.90	1,464,000.0	3,650.00
4	24.60	12.20	5.57	3.01	6.80	108,000.00	10,380.00
5	7.34	5.57	4.42	3.42	15.50	454,000.00	7,440.00
6	2.44	1.89	1.65	1.43	23.70	1,231,000.0	8,980.00
7	4.89	3.85	3.27	2.73	19.30	699,000.00	5,790.00
8	2.63	2.15	1.84	1.55	18.00	1,593,000.0	12,760.00
9	9.10	7.10	5.16	3.63	9.40	674,000.00	9,100.00
10	14.40	12.10	9.63	7.41	10.80	524,000.00	1,180.00
11	7.64	5.92	4.58	3.44	13.00	539,000.00	8,440.00

Figure 2-17. Overview of data editor after the FWD information is imported.

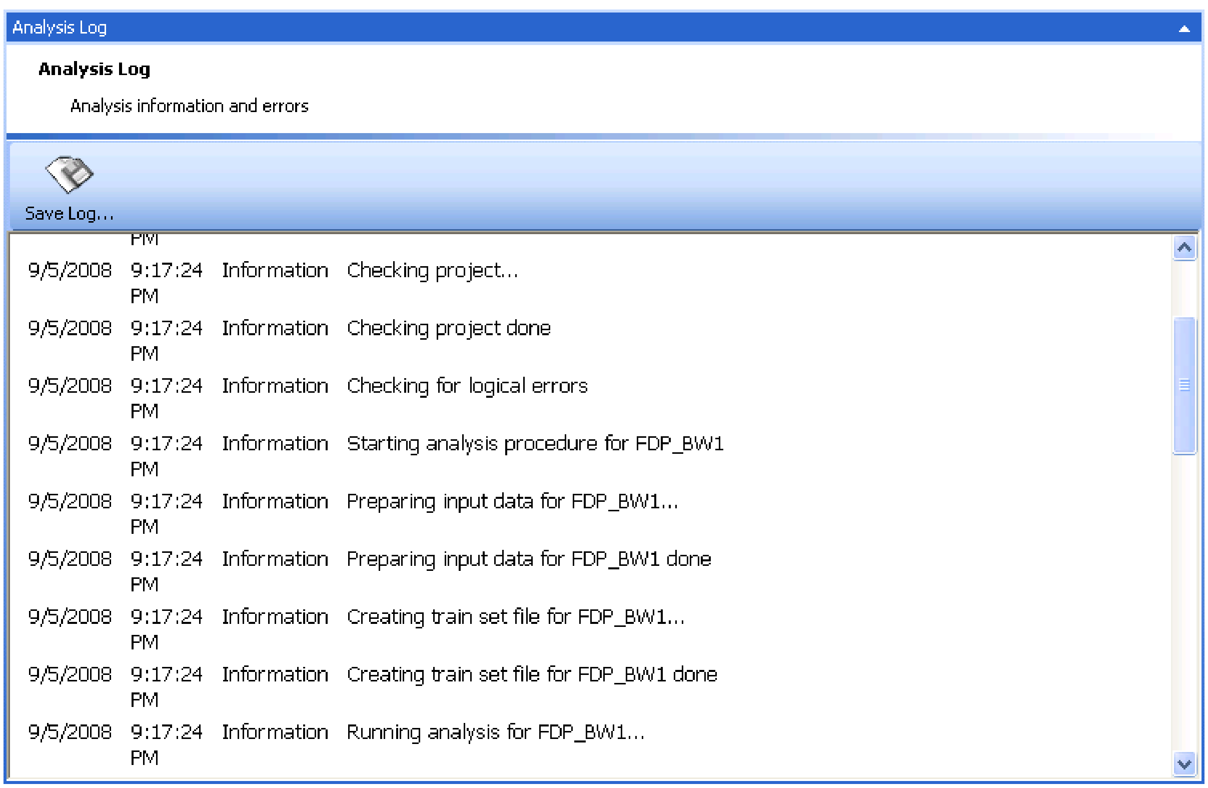
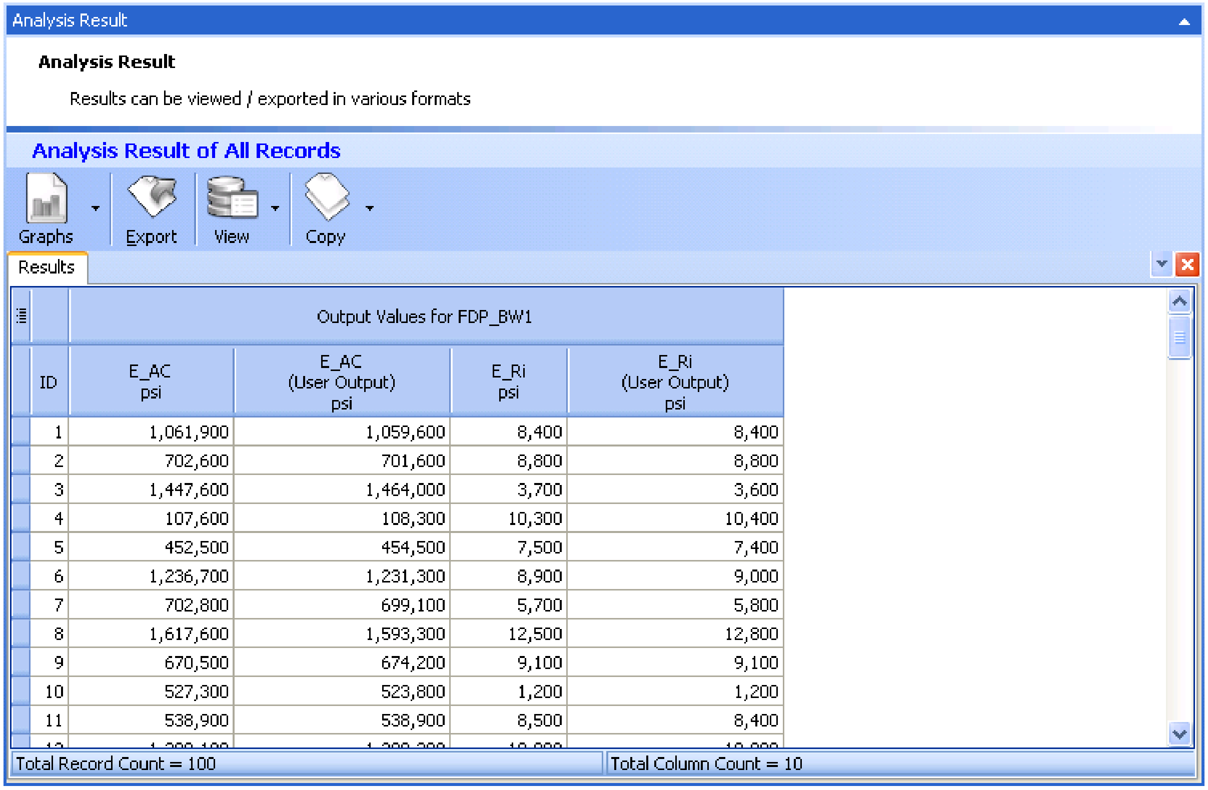


Figure 2-18. Run time screen to view the details of artificial neural network analysis.



ID	E_AC psi	E_AC (User Output) psi	E_Ri psi	E_Ri (User Output) psi
1	1,061,900	1,059,600	8,400	8,400
2	702,600	701,600	8,800	8,800
3	1,447,600	1,464,000	3,700	3,600
4	107,600	108,300	10,300	10,400
5	452,500	454,500	7,500	7,400
6	1,236,700	1,231,300	8,900	9,000
7	702,800	699,100	5,700	5,800
8	1,617,600	1,593,300	12,500	12,800
9	670,500	674,200	9,100	9,100
10	527,300	523,800	1,200	1,200
11	538,900	538,900	8,500	8,400

Figure 2-19. Viewing the results of FWD analysis in the data editor.

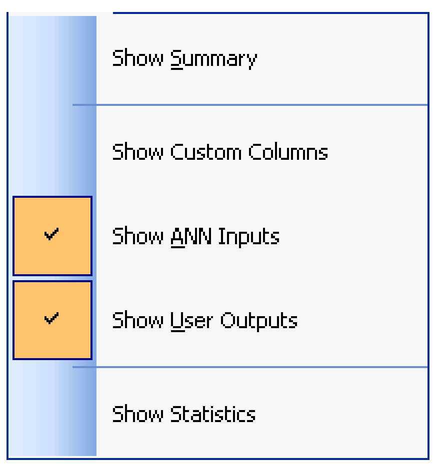
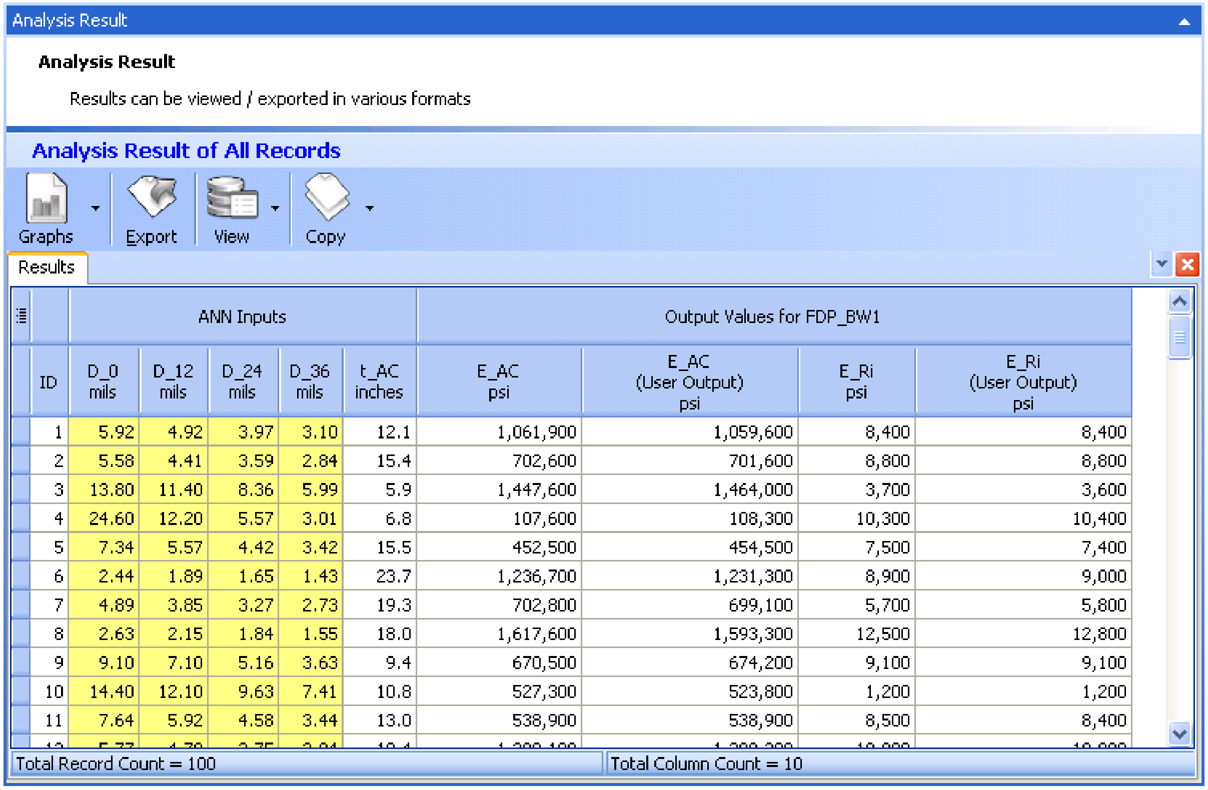


Figure 2-20. Options to view neural network analysis results.



Analysis Result

Analysis Result

Results can be viewed / exported in various formats

Analysis Result of All Records

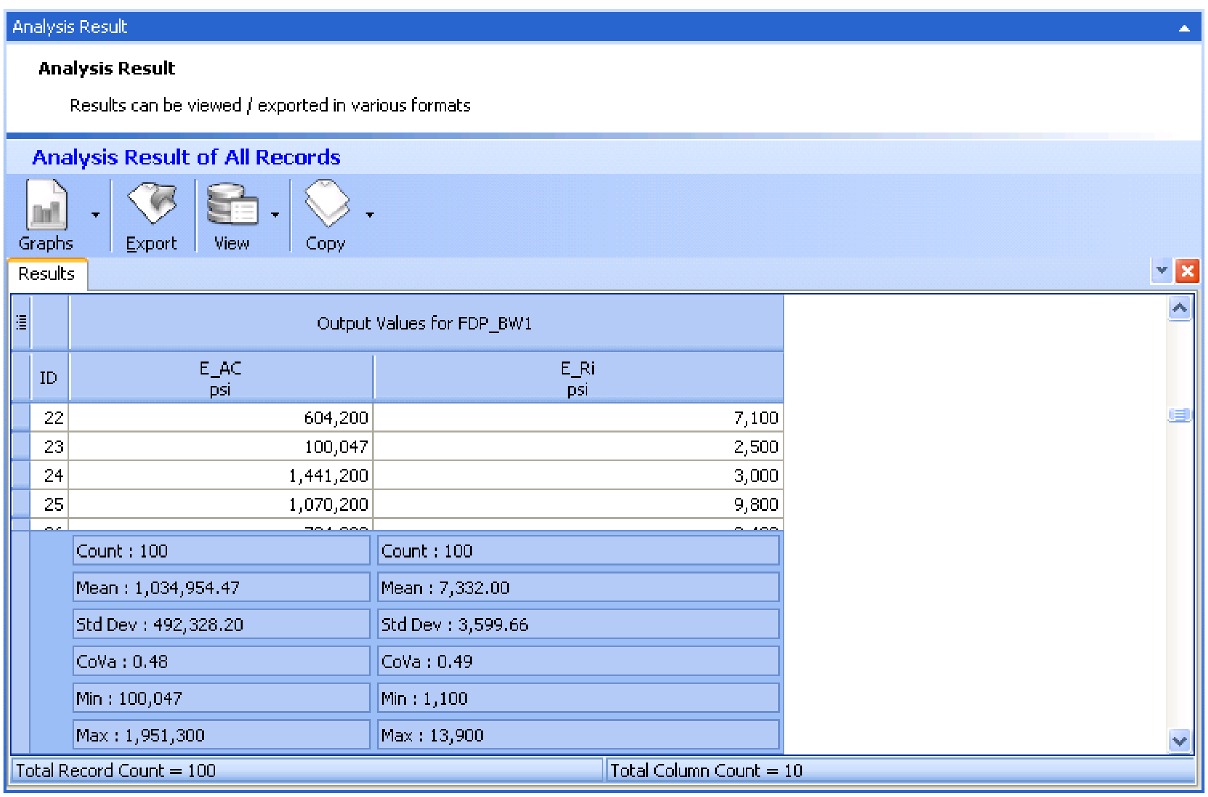
Graphs | Export | View | Copy

Results

	ANN Inputs					Output Values for FDP_BW1			
ID	D_0 mils	D_12 mils	D_24 mils	D_36 mils	t_AC inches	E_AC psi	E_AC (User Output) psi	E_Ri psi	E_Ri (User Output) psi
1	5.92	4.92	3.97	3.10	12.1	1,061,900	1,059,600	8,400	8,400
2	5.58	4.41	3.59	2.84	15.4	702,600	701,600	8,800	8,800
3	13.80	11.40	8.36	5.99	5.9	1,447,600	1,464,000	3,700	3,600
4	24.60	12.20	5.57	3.01	6.8	107,600	108,300	10,300	10,400
5	7.34	5.57	4.42	3.42	15.5	452,500	454,500	7,500	7,400
6	2.44	1.89	1.65	1.43	23.7	1,236,700	1,231,300	8,900	9,000
7	4.89	3.85	3.27	2.73	19.3	702,800	699,100	5,700	5,800
8	2.63	2.15	1.84	1.55	18.0	1,617,600	1,593,300	12,500	12,800
9	9.10	7.10	5.16	3.63	9.4	670,500	674,200	9,100	9,100
10	14.40	12.10	9.63	7.41	10.8	527,300	523,800	1,200	1,200
11	7.64	5.92	4.58	3.44	13.0	538,900	538,900	8,500	8,400

Total Record Count = 100 | Total Column Count = 10

Figure 2-21. Alternative view for results of FWD analysis.



Analysis Result

Analysis Result

Results can be viewed / exported in various formats

Analysis Result of All Records

Graphs | Export | View | Copy

Results

	Output Values for FDP_BW1	
ID	E_AC psi	E_Ri psi
22	604,200	7,100
23	100,047	2,500
24	1,441,200	3,000
25	1,070,200	9,800
	Count : 100	Count : 100
	Mean : 1,034,954.47	Mean : 7,332.00
	Std Dev : 492,328.20	Std Dev : 3,599.66
	CoVa : 0.48	CoVa : 0.49
	Min : 100,047	Min : 1,100
	Max : 1,951,300	Max : 13,900

Total Record Count = 100 | Total Column Count = 10

Figure 2-22. Statistical summary of FWD findings through ANN-Pro.

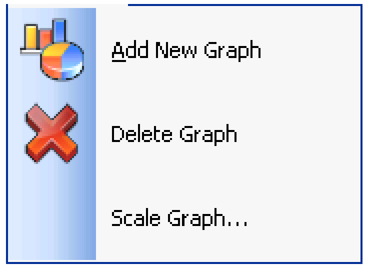


Figure 2-23. Adding a graph for enhanced view of results.

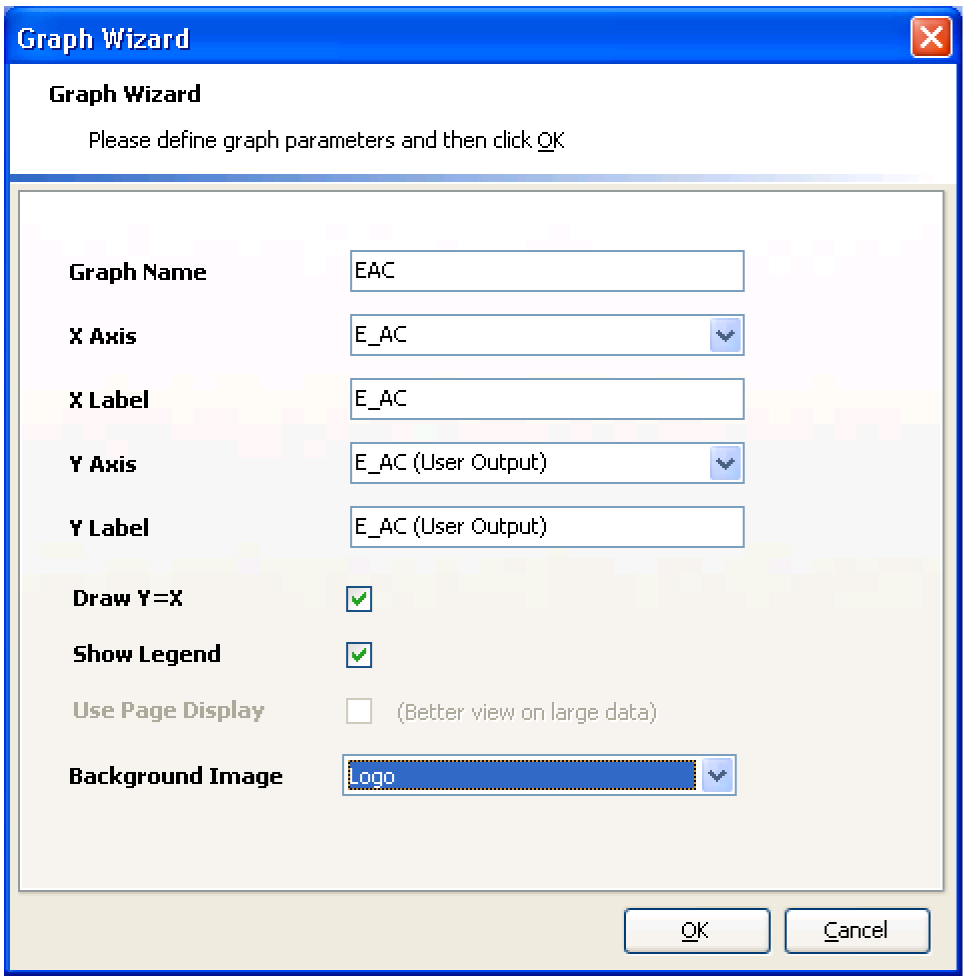


Figure 2-24. Graph wizard to plot the backcalculated results of FWD stations.

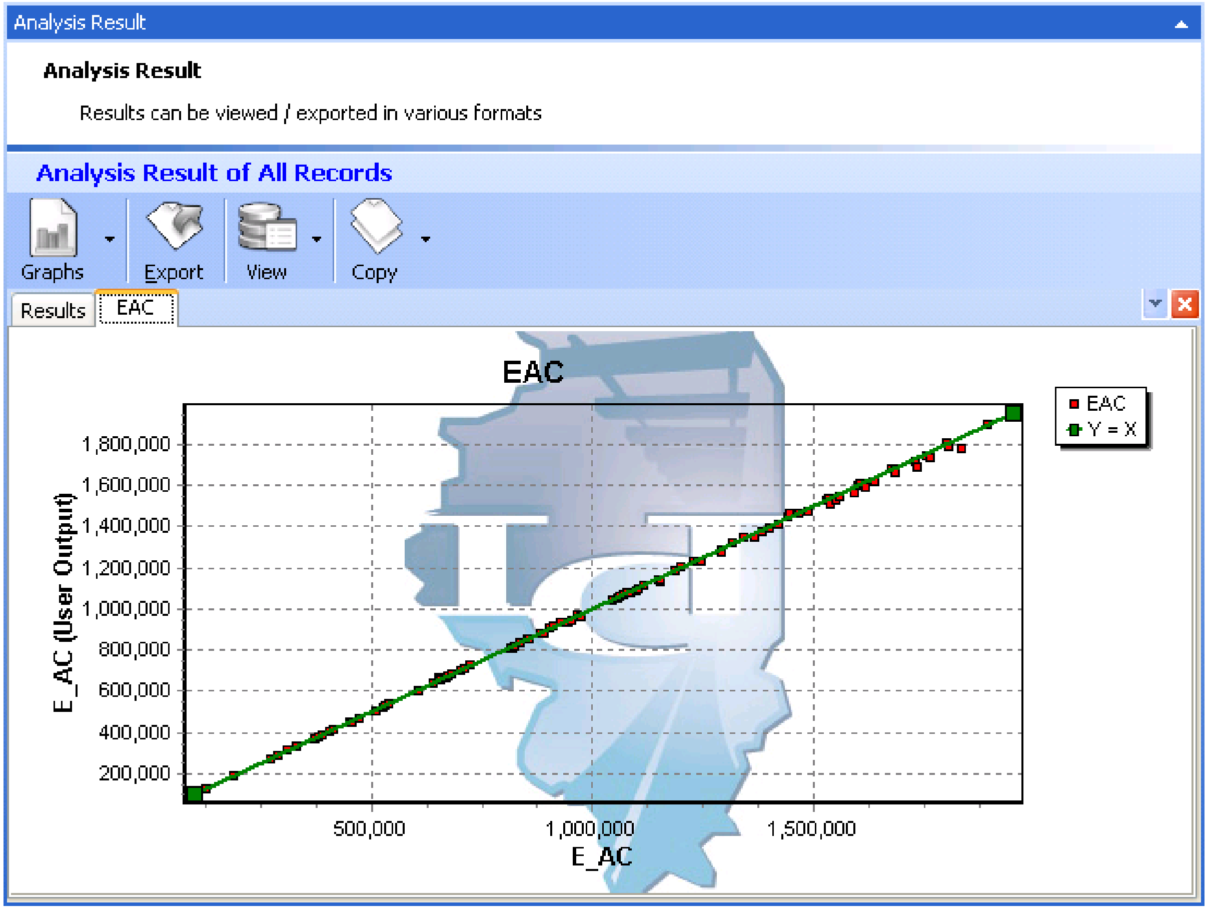


Figure 2-25. Comparison of analysis results with ILLI-PAVE finite element solutions.

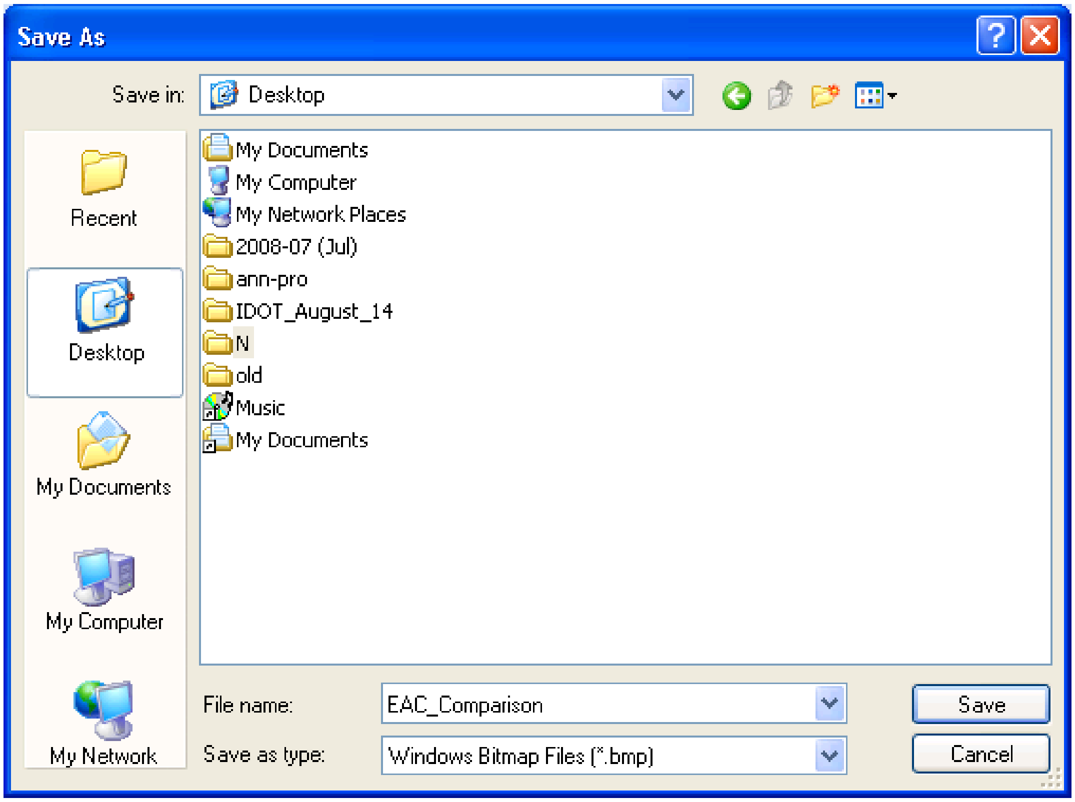


Figure 2-26. Exporting graphs as Windows bitmap files.

CHAPTER 3: EXTRA FEATURES

ANN-Pro includes many features that enhance the capabilities of the software program. These features are mainly implemented to provide better organization, comfort and efficiency within the software. During development stage, the program was modified many times based on the feedback obtained from end users. Accordingly, some components of the program were rewritten and many advanced features were added. For example, the capability of importing and exporting FWD analysis data from MS Excel has been incorporated. Copy and paste from the MS Excel directly to ANN-Pro was made possible. An advanced importing option that enables users to bring irregularly formatted data into software was also included. The visualization of the data in the form of graphs was enhanced so that essential data and analysis graphs can directly be exported to reports. In addition, crucial statistical information, such as the mean, standard deviation, etc. of the FWD analysis results has been added to the output of ANN-Pro. The latest improvement in the software now offers the use of scripts to edit the FWD data based on user needs. In the following section, the utilization of some of these features will be explained in detail.

IMPORTING DATA FROM JILS FWD MACHINE

ANN-Pro can utilize JILS data for FWD backcalculation purposes. First, ANN structural model needs to be specified as explained in the previous section. The following steps are necessary to successfully import the data (sample JILS file is distributed with setup file.

- In the Data Editor, Import JILS Data option is clicked and JILS data needs to be selected (Figure 3-1).
- When the data file is selected, ANN-Pro automatically determines the column headings of JILS FWD output data file. Then, the user can match these columns with the ones defined in ANN-Pro structural model (Figure 3-2). Corresponding columns can be selected in Data File Columns and ANN Model Columns separately and Join button is clicked for each variable in the model. The matched columns are shown in the link info screen. (Figure 3-3). Data from JILS file is automatically normalized to 9000 lbs.

The same feature can also be used to import FWD data readily available in MS Excel. (Import Data -> Special Import) To use this feature, FWD data available in MS Excel should be separated according to columns. Each variable needs to have a heading so that ANN-Pro can distinguish each variable of the structural model. In other words, Special Import is used when matching of columns is desired. The steps explained in Figures 3-1 to 3-3 can be repeated with the properly formatted Excel file.

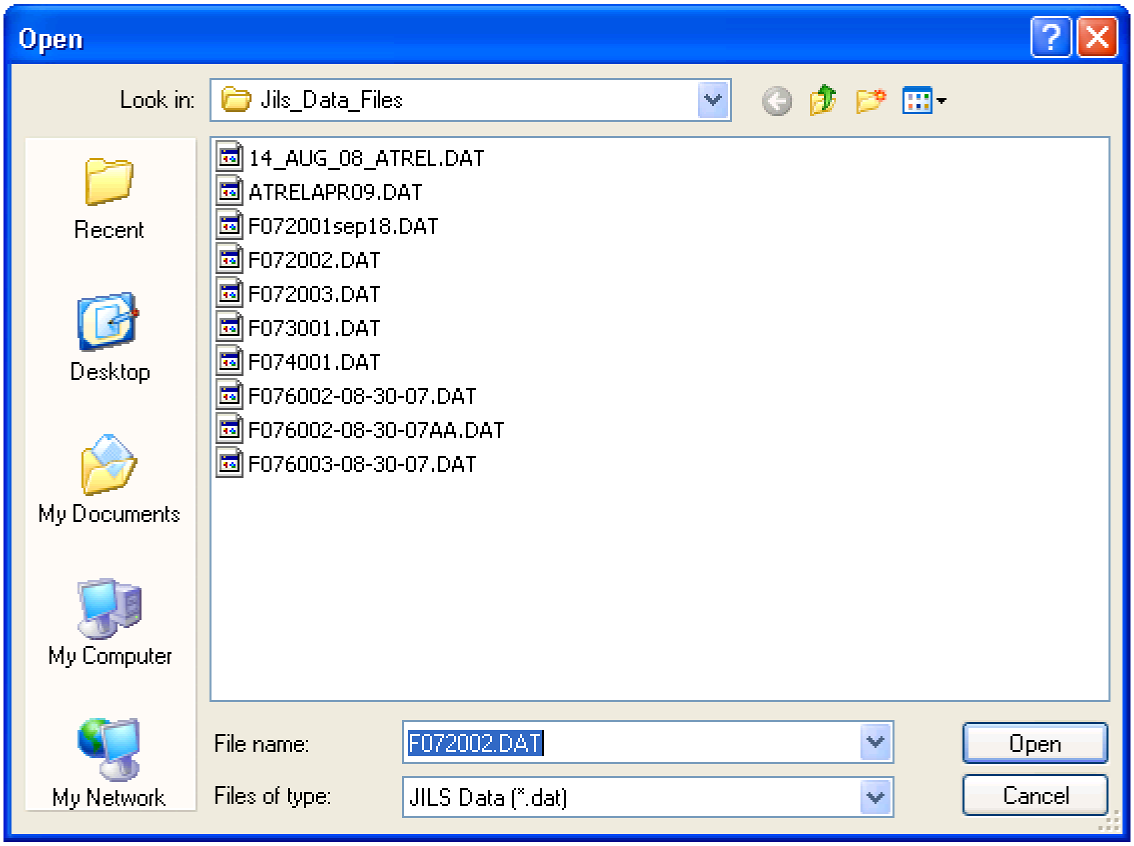


Figure 3-1. JILS FWD Data file selection in ANN-Pro.

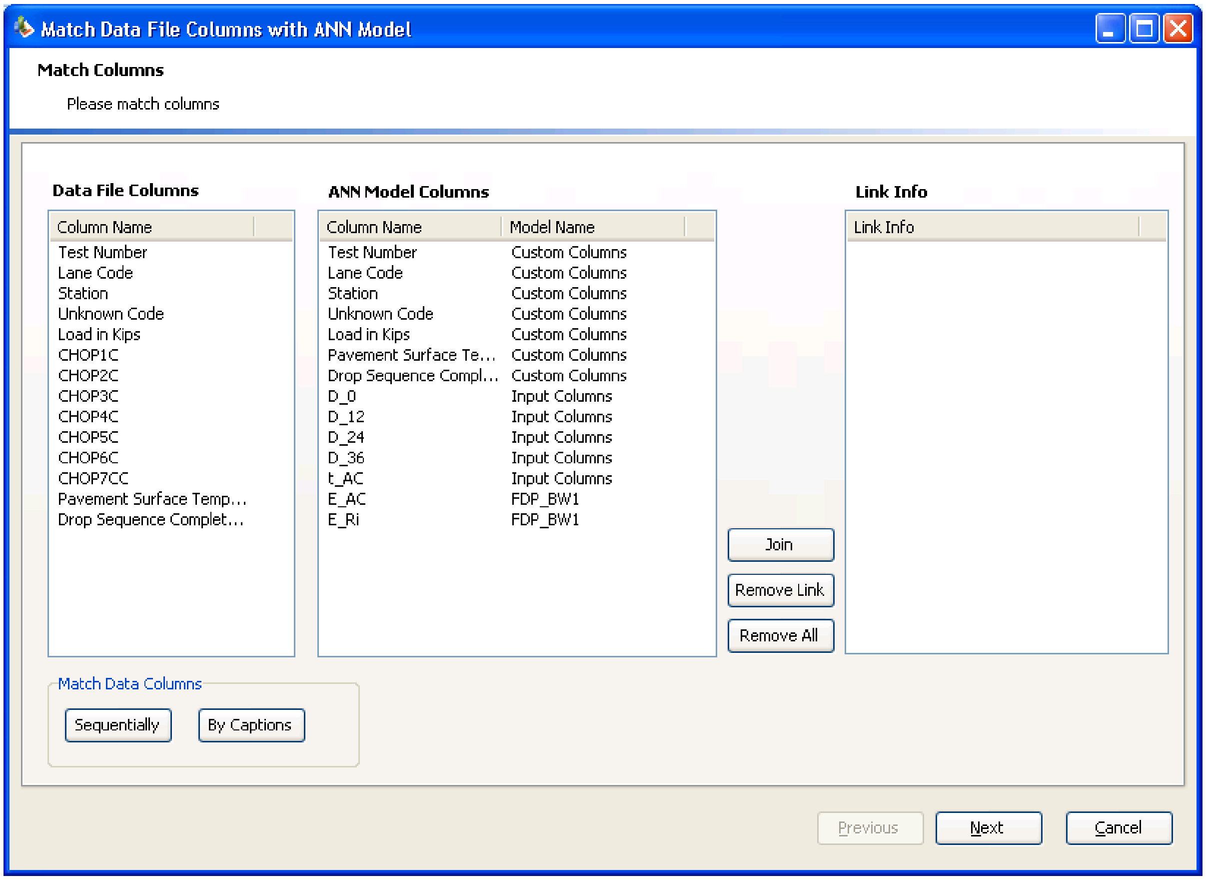


Figure 3-2. ANN structural model columns with data file columns.

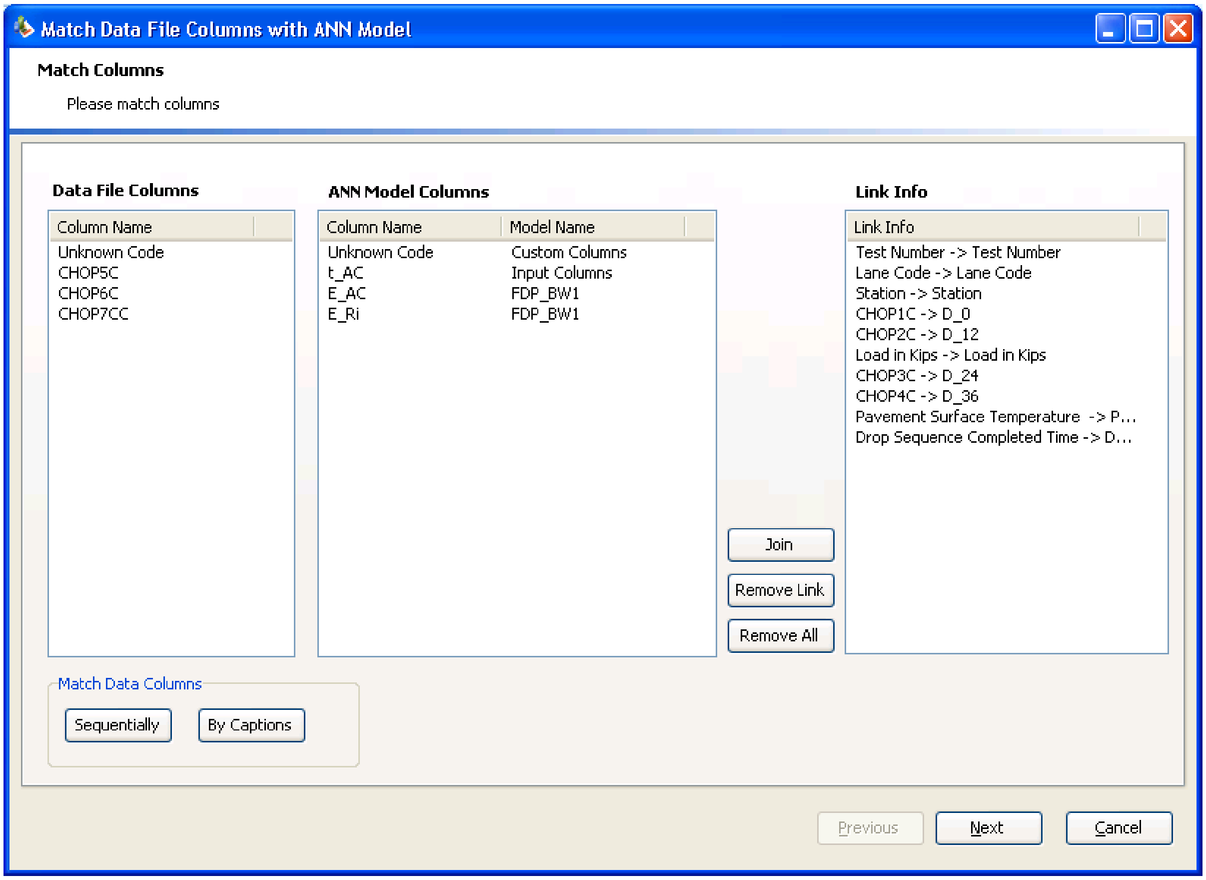


Figure 3-3. Observation of link between ANN Model and data file.

DIRECT COPY AND PASTE

Importing Data

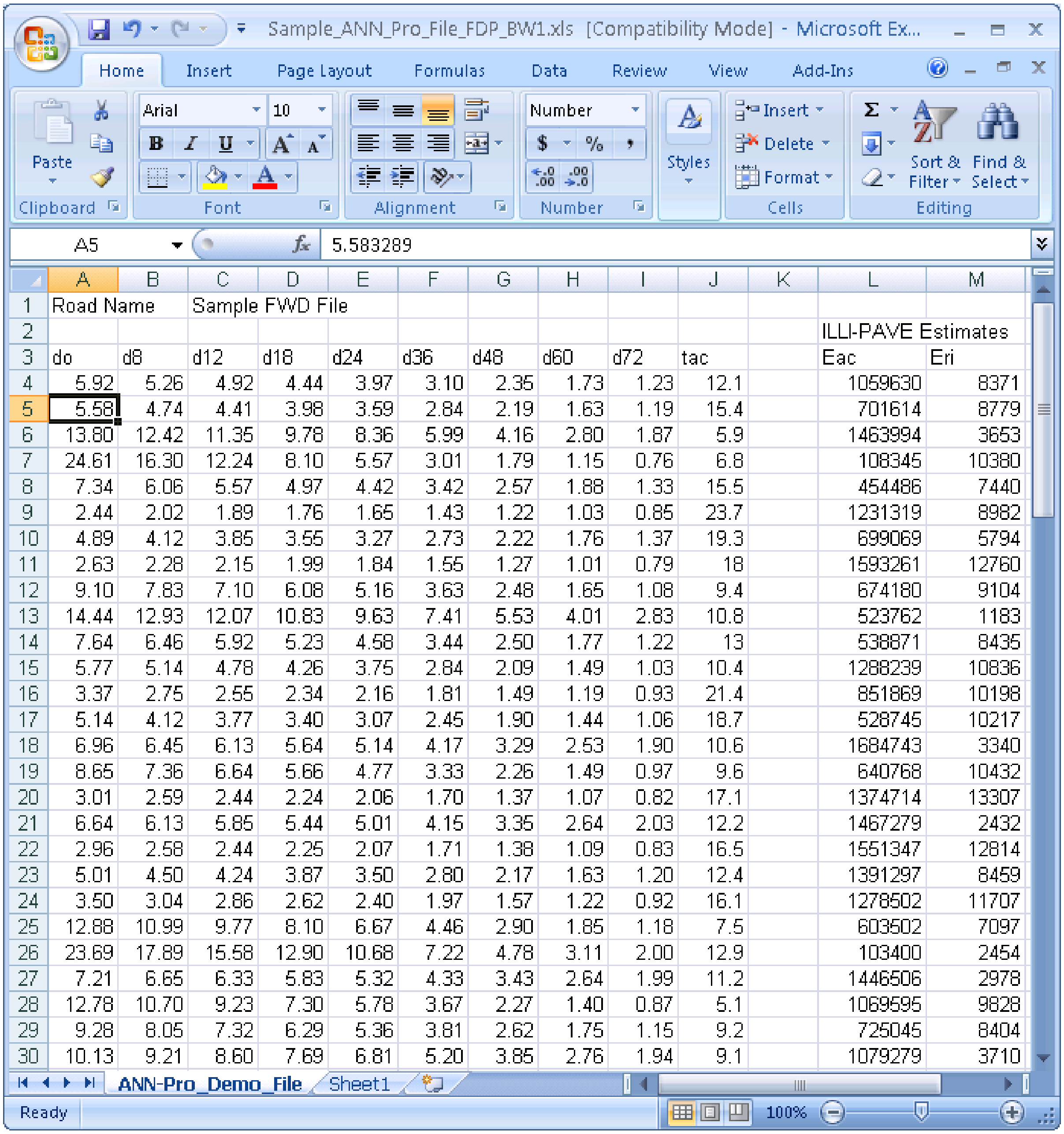
ANN-Pro provides variety of options for importing data from MS Excel. Among all these, direct copy and paste option may be the easiest for end users. Since ANN-Pro is a Windows operating system based software, the user is expected to be familiar with the copy and paste feature existing in all Microsoft based software products.

To illustrate the irregular data import using direct copy and paste, FWD analysis for backcalculation of full depth asphalt pavement properties is repeated here. Since the same problem was already described in the previous section, only the data editor part will be explained. Figure 3-4 shows the format of FWD data available in MS Excel. The data columns D0, D12, D24, D36 and tAC are the necessary ones for the execution of FDP-BW1. The steps to copy the data for the first 11 stations are explained below (sample Excel file is distributed with setup file):

1. In the MS Excel file, choose the column D0 and the first 11 FWD station data by selecting them with the mouse. The selected area will then be highlighted (Figure 3-5).
2. Go to Data Editor of ANN-Pro (assuming that the FDP-BW1 model is already specified and data editor menu is shown on the screen) and click Paste button available on the data editor toolbar (Figure 3-6). Notice that all the cells in ANN-Pro

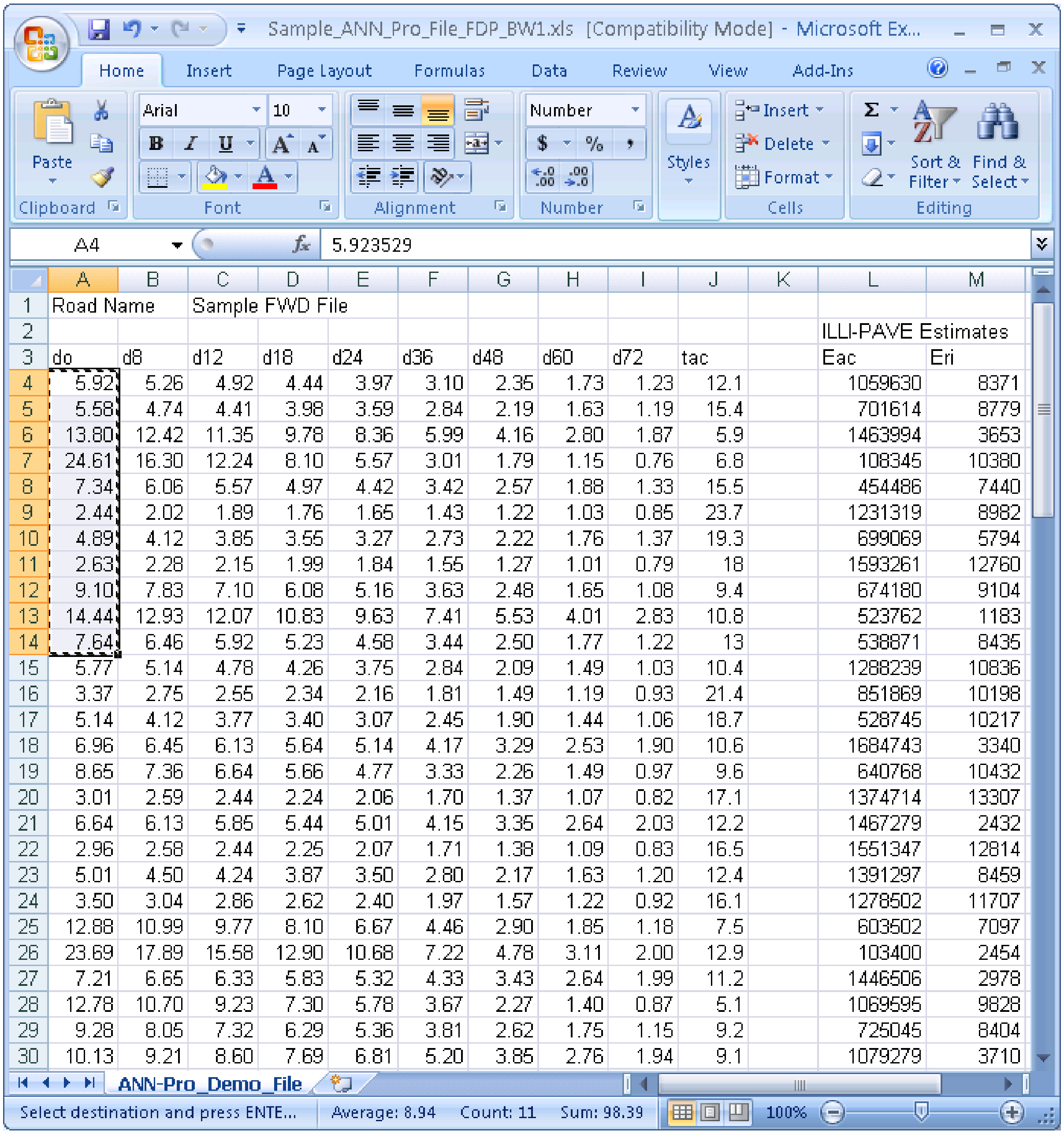
will be highlighted red, since ANN-Pro internally checks if all the column values were entered or not. If any of the inputs were not entered or shown as zero, the cells will be indicated as red. Then go to MS Excel file again. This time, chose the column D12 and the first 11 FWD station data by selecting them with mouse. The selected area will be highlighted. Go to ANN-Pro Data Editor and click on the column heading "D_12". Then right click or use menus to copy. The column will be selected and highlighted. Click on paste in this condition. This procedure can be repeated for all the data columns.

3. Another option is that user can select multiple columns in MS Excel and copy this data (Figure 3-7).
4. Multiple data columns can then be pasted into Ann-Pro directly using paste button (Figure 3-8).
5. After all of them are imported into the program, the cells will be colored as white, showing that the project is ready to be analyzed. Thickness can be input manually or by using the Set Selection Value Button, if desired.
6. The user can refer to the previous section for the other steps for conducting ANN analysis.



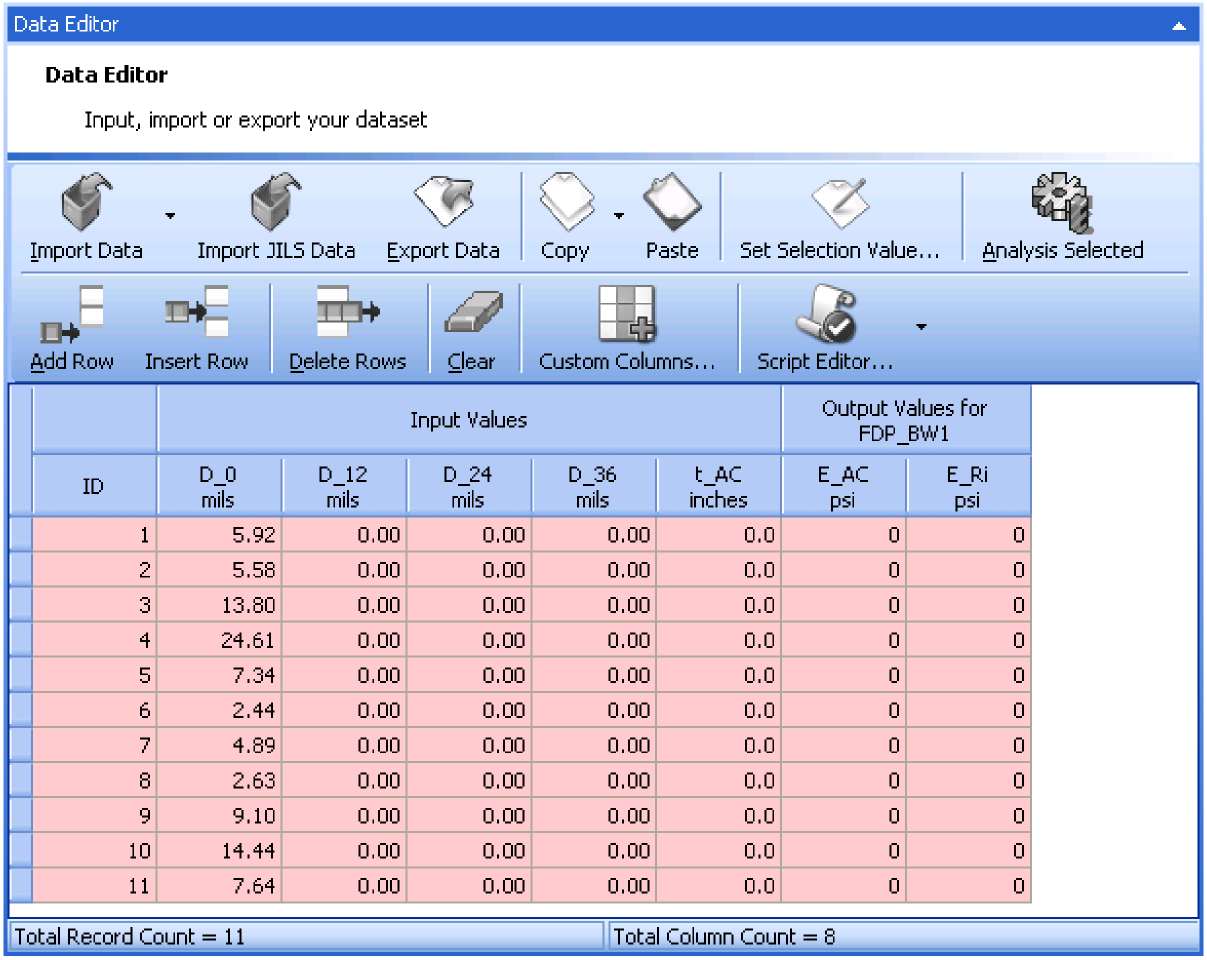
	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Road Name		Sample FWD File										
2												ILLI-PAVE Estimates	
3	do	d8	d12	d18	d24	d36	d48	d60	d72	tac		Eac	Eri
4	5.92	5.26	4.92	4.44	3.97	3.10	2.35	1.73	1.23	12.1		1059630	8371
5	5.58	4.74	4.41	3.98	3.59	2.84	2.19	1.63	1.19	15.4		701614	8779
6	13.80	12.42	11.35	9.78	8.36	5.99	4.16	2.80	1.87	5.9		1463994	3653
7	24.61	16.30	12.24	8.10	5.57	3.01	1.79	1.15	0.76	6.8		108345	10380
8	7.34	6.06	5.57	4.97	4.42	3.42	2.57	1.88	1.33	15.5		454486	7440
9	2.44	2.02	1.89	1.76	1.65	1.43	1.22	1.03	0.85	23.7		1231319	8982
10	4.89	4.12	3.85	3.55	3.27	2.73	2.22	1.76	1.37	19.3		699069	5794
11	2.63	2.28	2.15	1.99	1.84	1.55	1.27	1.01	0.79	18		1593261	12760
12	9.10	7.83	7.10	6.08	5.16	3.63	2.48	1.65	1.08	9.4		674180	9104
13	14.44	12.93	12.07	10.83	9.63	7.41	5.53	4.01	2.83	10.8		523762	1183
14	7.64	6.46	5.92	5.23	4.58	3.44	2.50	1.77	1.22	13		538871	8435
15	5.77	5.14	4.78	4.26	3.75	2.84	2.09	1.49	1.03	10.4		1288239	10836
16	3.37	2.75	2.55	2.34	2.16	1.81	1.49	1.19	0.93	21.4		851869	10198
17	5.14	4.12	3.77	3.40	3.07	2.45	1.90	1.44	1.06	18.7		528745	10217
18	6.96	6.45	6.13	5.64	5.14	4.17	3.29	2.53	1.90	10.6		1684743	3340
19	8.65	7.36	6.64	5.66	4.77	3.33	2.26	1.49	0.97	9.6		640768	10432
20	3.01	2.59	2.44	2.24	2.06	1.70	1.37	1.07	0.82	17.1		1374714	13307
21	6.64	6.13	5.85	5.44	5.01	4.15	3.35	2.64	2.03	12.2		1467279	2432
22	2.96	2.58	2.44	2.25	2.07	1.71	1.38	1.09	0.83	16.5		1551347	12814
23	5.01	4.50	4.24	3.87	3.50	2.80	2.17	1.63	1.20	12.4		1391297	8459
24	3.50	3.04	2.86	2.62	2.40	1.97	1.57	1.22	0.92	16.1		1278502	11707
25	12.88	10.99	9.77	8.10	6.67	4.46	2.90	1.85	1.18	7.5		603502	7097
26	23.69	17.89	15.58	12.90	10.68	7.22	4.78	3.11	2.00	12.9		103400	2454
27	7.21	6.65	6.33	5.83	5.32	4.33	3.43	2.64	1.99	11.2		1446506	2978
28	12.78	10.70	9.23	7.30	5.78	3.67	2.27	1.40	0.87	5.1		1069595	9828
29	9.28	8.05	7.32	6.29	5.36	3.81	2.62	1.75	1.15	9.2		725045	8404
30	10.13	9.21	8.60	7.69	6.81	5.20	3.85	2.76	1.94	9.1		1079279	3710

Figure 3-4. Sample Excel file to import FWD data by copy and paste.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Road Name		Sample FWD File										
2												ILLI-PAVE Estimates	
3	do	d8	d12	d18	d24	d36	d48	d60	d72	tac		Eac	Eri
4	5.92	5.26	4.92	4.44	3.97	3.10	2.35	1.73	1.23	12.1		1059630	8371
5	5.58	4.74	4.41	3.98	3.59	2.84	2.19	1.63	1.19	15.4		701614	8779
6	13.80	12.42	11.35	9.78	8.36	5.99	4.16	2.80	1.87	5.9		1463994	3653
7	24.61	16.30	12.24	8.10	5.57	3.01	1.79	1.15	0.76	6.8		108345	10380
8	7.34	6.06	5.57	4.97	4.42	3.42	2.57	1.88	1.33	15.5		454486	7440
9	2.44	2.02	1.89	1.76	1.65	1.43	1.22	1.03	0.85	23.7		1231319	8982
10	4.89	4.12	3.85	3.55	3.27	2.73	2.22	1.76	1.37	19.3		699069	5794
11	2.63	2.28	2.15	1.99	1.84	1.55	1.27	1.01	0.79	18		1593261	12760
12	9.10	7.83	7.10	6.08	5.16	3.63	2.48	1.65	1.08	9.4		674180	9104
13	14.44	12.93	12.07	10.83	9.63	7.41	5.53	4.01	2.83	10.8		523762	1183
14	7.64	6.46	5.92	5.23	4.58	3.44	2.50	1.77	1.22	13		538871	8435
15	5.77	5.14	4.78	4.26	3.75	2.84	2.09	1.49	1.03	10.4		1288239	10836
16	3.37	2.75	2.55	2.34	2.16	1.81	1.49	1.19	0.93	21.4		851869	10198
17	5.14	4.12	3.77	3.40	3.07	2.45	1.90	1.44	1.06	18.7		528745	10217
18	6.96	6.45	6.13	5.64	5.14	4.17	3.29	2.53	1.90	10.6		1684743	3340
19	8.65	7.36	6.64	5.66	4.77	3.33	2.26	1.49	0.97	9.6		640768	10432
20	3.01	2.59	2.44	2.24	2.06	1.70	1.37	1.07	0.82	17.1		1374714	13307
21	6.64	6.13	5.85	5.44	5.01	4.15	3.35	2.64	2.03	12.2		1467279	2432
22	2.96	2.58	2.44	2.25	2.07	1.71	1.38	1.09	0.83	16.5		1551347	12814
23	5.01	4.50	4.24	3.87	3.50	2.80	2.17	1.63	1.20	12.4		1391297	8459
24	3.50	3.04	2.86	2.62	2.40	1.97	1.57	1.22	0.92	16.1		1278502	11707
25	12.88	10.99	9.77	8.10	6.67	4.46	2.90	1.85	1.18	7.5		603502	7097
26	23.69	17.89	15.58	12.90	10.68	7.22	4.78	3.11	2.00	12.9		103400	2454
27	7.21	6.65	6.33	5.83	5.32	4.33	3.43	2.64	1.99	11.2		1446506	2978
28	12.78	10.70	9.23	7.30	5.78	3.67	2.27	1.40	0.87	5.1		1069595	9828
29	9.28	8.05	7.32	6.29	5.36	3.81	2.62	1.75	1.15	9.2		725045	8404
30	10.13	9.21	8.60	7.69	6.81	5.20	3.85	2.76	1.94	9.1		1079279	3710

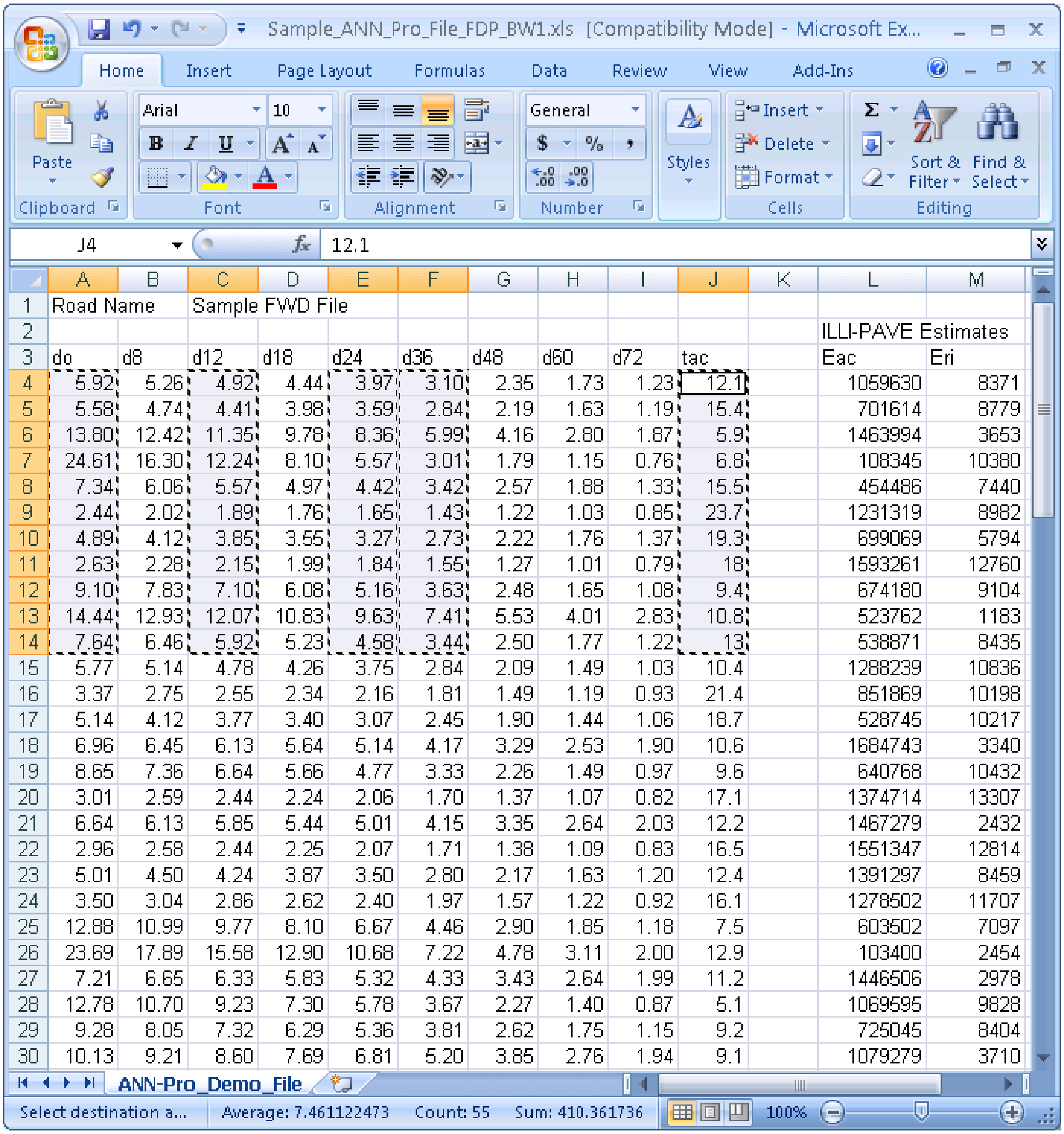
Figure 3-5. Selection of the first data column for direct copy and paste.



	Input Values					Output Values for FDP_BW1	
ID	D_0 mils	D_12 mils	D_24 mils	D_36 mils	t_AC inches	E_AC psi	E_Ri psi
1	5.92	0.00	0.00	0.00	0.0	0	0
2	5.58	0.00	0.00	0.00	0.0	0	0
3	13.80	0.00	0.00	0.00	0.0	0	0
4	24.61	0.00	0.00	0.00	0.0	0	0
5	7.34	0.00	0.00	0.00	0.0	0	0
6	2.44	0.00	0.00	0.00	0.0	0	0
7	4.89	0.00	0.00	0.00	0.0	0	0
8	2.63	0.00	0.00	0.00	0.0	0	0
9	9.10	0.00	0.00	0.00	0.0	0	0
10	14.44	0.00	0.00	0.00	0.0	0	0
11	7.64	0.00	0.00	0.00	0.0	0	0

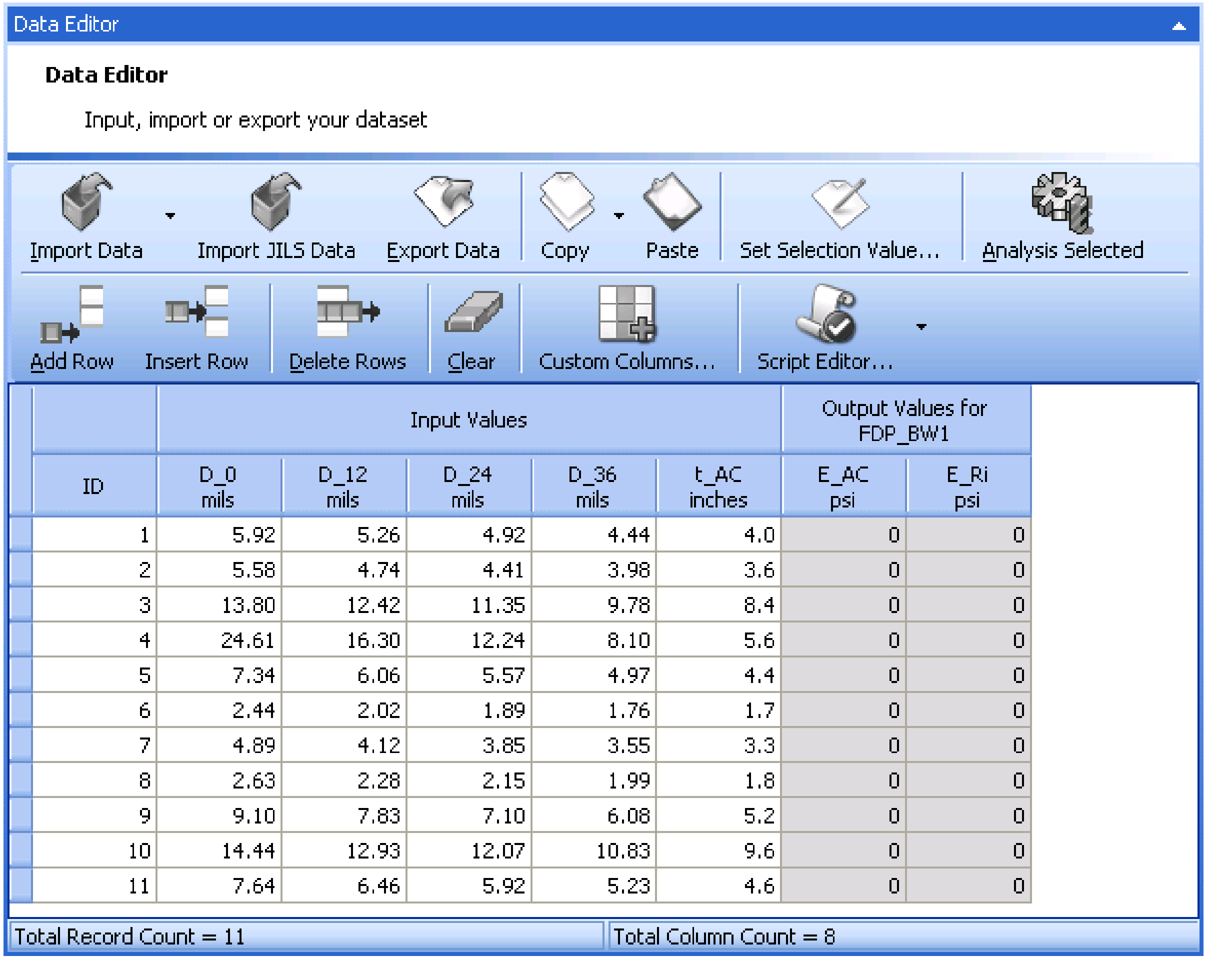
Total Record Count = 11 Total Column Count = 8

Figure 3-6. Pasting the first column from MS Excel to ANN-Pro data editor.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Road Name		Sample FWD File										
2												ILLI-PAVE Estimates	
3	do	d8	d12	d18	d24	d36	d48	d60	d72	tac		Eac	Eri
4	5.92	5.26	4.92	4.44	3.97	3.10	2.35	1.73	1.23	12.1		1059630	8371
5	5.58	4.74	4.41	3.98	3.59	2.84	2.19	1.63	1.19	15.4		701614	8779
6	13.80	12.42	11.35	9.78	8.36	5.99	4.16	2.80	1.87	5.9		1463994	3653
7	24.61	16.30	12.24	8.10	5.57	3.01	1.79	1.15	0.76	6.8		108345	10380
8	7.34	6.06	5.57	4.97	4.42	3.42	2.57	1.88	1.33	15.5		454486	7440
9	2.44	2.02	1.89	1.76	1.65	1.43	1.22	1.03	0.85	23.7		1231319	8982
10	4.89	4.12	3.85	3.55	3.27	2.73	2.22	1.76	1.37	19.3		699069	5794
11	2.63	2.28	2.15	1.99	1.84	1.55	1.27	1.01	0.79	18		1593261	12760
12	9.10	7.83	7.10	6.08	5.16	3.63	2.48	1.65	1.08	9.4		674180	9104
13	14.44	12.93	12.07	10.83	9.63	7.41	5.53	4.01	2.83	10.8		523762	1183
14	7.64	6.46	5.92	5.23	4.58	3.44	2.50	1.77	1.22	13		538871	8435
15	5.77	5.14	4.78	4.26	3.75	2.84	2.09	1.49	1.03	10.4		1288239	10836
16	3.37	2.75	2.55	2.34	2.16	1.81	1.49	1.19	0.93	21.4		851869	10198
17	5.14	4.12	3.77	3.40	3.07	2.45	1.90	1.44	1.06	18.7		528745	10217
18	6.96	6.45	6.13	5.64	5.14	4.17	3.29	2.53	1.90	10.6		1684743	3340
19	8.65	7.36	6.64	5.66	4.77	3.33	2.26	1.49	0.97	9.6		640768	10432
20	3.01	2.59	2.44	2.24	2.06	1.70	1.37	1.07	0.82	17.1		1374714	13307
21	6.64	6.13	5.85	5.44	5.01	4.15	3.35	2.64	2.03	12.2		1467279	2432
22	2.96	2.58	2.44	2.25	2.07	1.71	1.38	1.09	0.83	16.5		1551347	12814
23	5.01	4.50	4.24	3.87	3.50	2.80	2.17	1.63	1.20	12.4		1391297	8459
24	3.50	3.04	2.86	2.62	2.40	1.97	1.57	1.22	0.92	16.1		1278502	11707
25	12.88	10.99	9.77	8.10	6.67	4.46	2.90	1.85	1.18	7.5		603502	7097
26	23.69	17.89	15.58	12.90	10.68	7.22	4.78	3.11	2.00	12.9		103400	2454
27	7.21	6.65	6.33	5.83	5.32	4.33	3.43	2.64	1.99	11.2		1446506	2978
28	12.78	10.70	9.23	7.30	5.78	3.67	2.27	1.40	0.87	5.1		1069595	9828
29	9.28	8.05	7.32	6.29	5.36	3.81	2.62	1.75	1.15	9.2		725045	8404
30	10.13	9.21	8.60	7.69	6.81	5.20	3.85	2.76	1.94	9.1		1079279	3710

Figure 3-7. Selection of the multiple data columns for direct copy and paste.



	Input Values					Output Values for FDP_BW1	
ID	D_0 mils	D_12 mils	D_24 mils	D_36 mils	t_AC inches	E_AC psi	E_Ri psi
1	5.92	5.26	4.92	4.44	4.0	0	0
2	5.58	4.74	4.41	3.98	3.6	0	0
3	13.80	12.42	11.35	9.78	8.4	0	0
4	24.61	16.30	12.24	8.10	5.6	0	0
5	7.34	6.06	5.57	4.97	4.4	0	0
6	2.44	2.02	1.89	1.76	1.7	0	0
7	4.89	4.12	3.85	3.55	3.3	0	0
8	2.63	2.28	2.15	1.99	1.8	0	0
9	9.10	7.83	7.10	6.08	5.2	0	0
10	14.44	12.93	12.07	10.83	9.6	0	0
11	7.64	6.46	5.92	5.23	4.6	0	0

Figure 3-8. Pasting multiple columns from MS Excel to ANN-Pro data editor.

Exporting Data

The direct copy and paste can also be used to extract data from ANN-Pro to MS Excel. The following steps show how to export the results of FWD backcalculation analysis on to MS Excel sheets.

1. The ANN structural model inputs need to be entered fully to properly run FWD analysis (Figure 3-9). Assuming that the FWD backcalculation analysis was performed successfully, the results need to be exported to MS Excel (Figure 3-10).
2. The data available in the results toolbar is selected with mouse similar to MS Excel (Figure 3-11). Then use the Copy button on the toolbar to copy all the data.
3. Open a blank Excel sheet and bring the cursor into any of the cells and then right click or use menus to paste the data (Figure 3-12).
4. If the user wants to export all the data in the data editor including the column headings, then click on Export in the results toolbar. Then, Save As screen appears (Figure 3-13). The results can be exported in different formats including MS Excel (.xls), Comma Separated File (.csv), and Web page file (.html or .xml).
5. Then the resultant file is opened in MS Excel (Figure 3-14) if the data are exported using “xls” file format. Windows Notepad or Wordpad programs can be used to view files with the “txt” extension. Similarly, Internet Explorer or Mozilla Internet browsers show “html” or “xml” files.

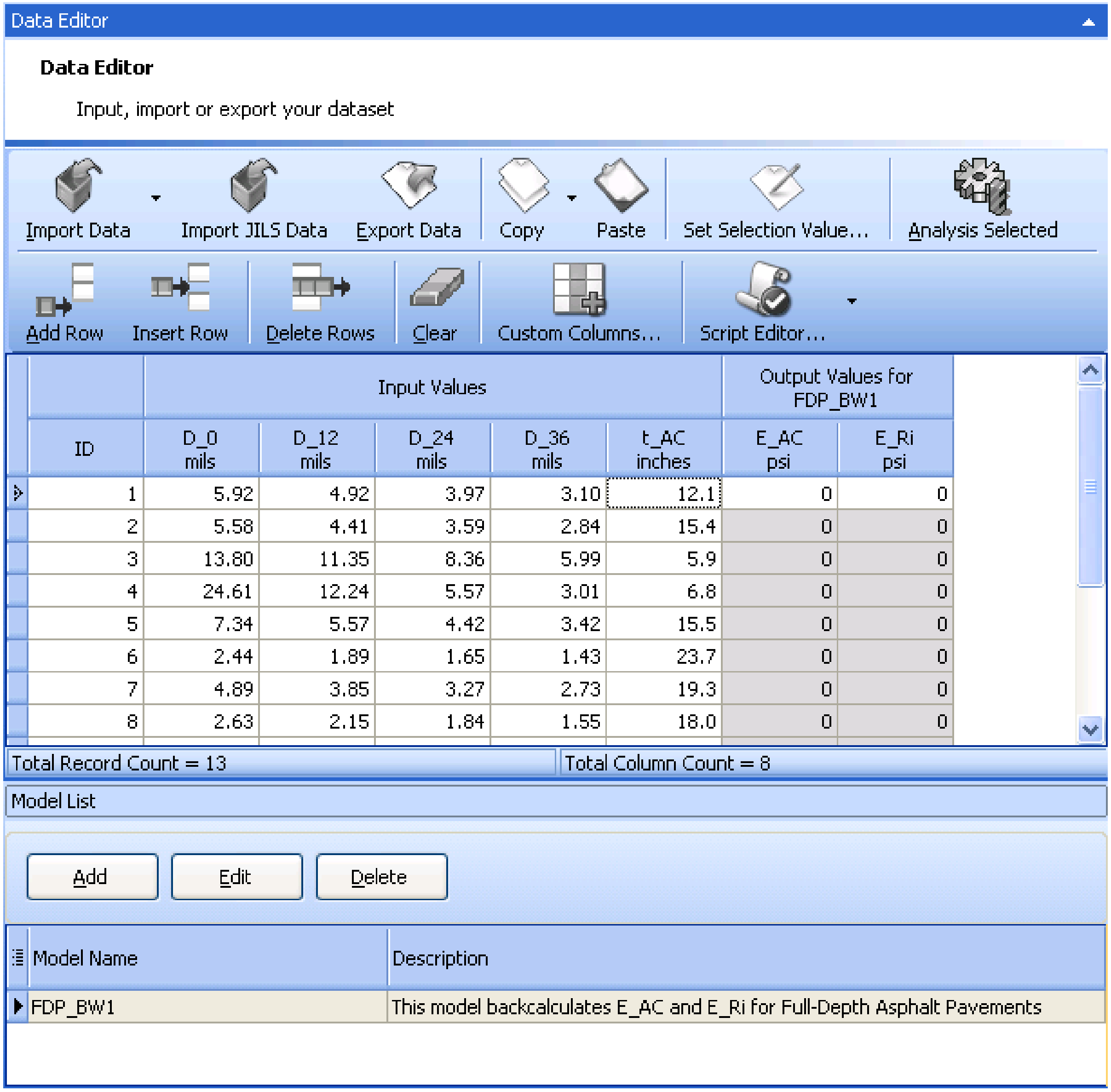
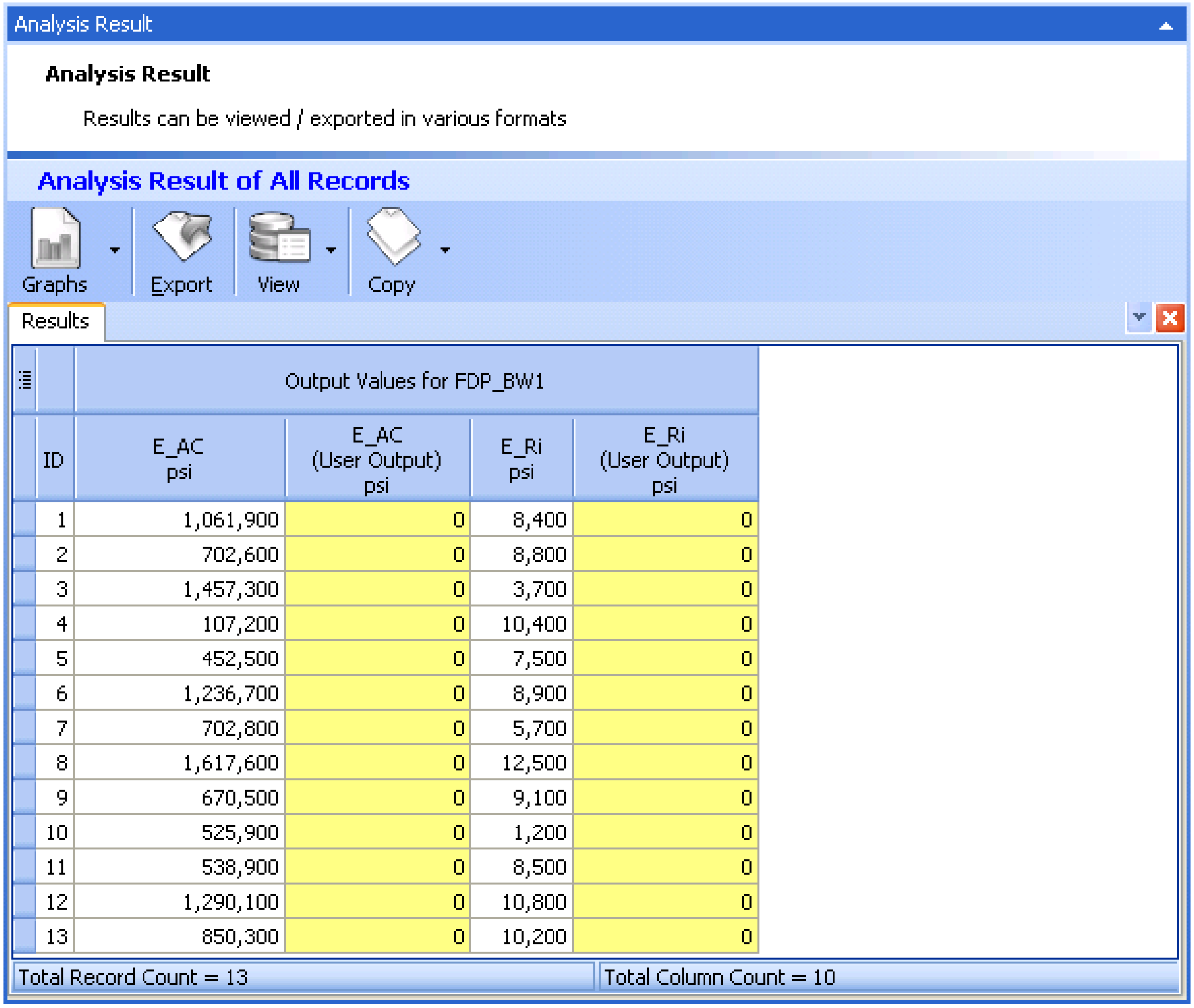
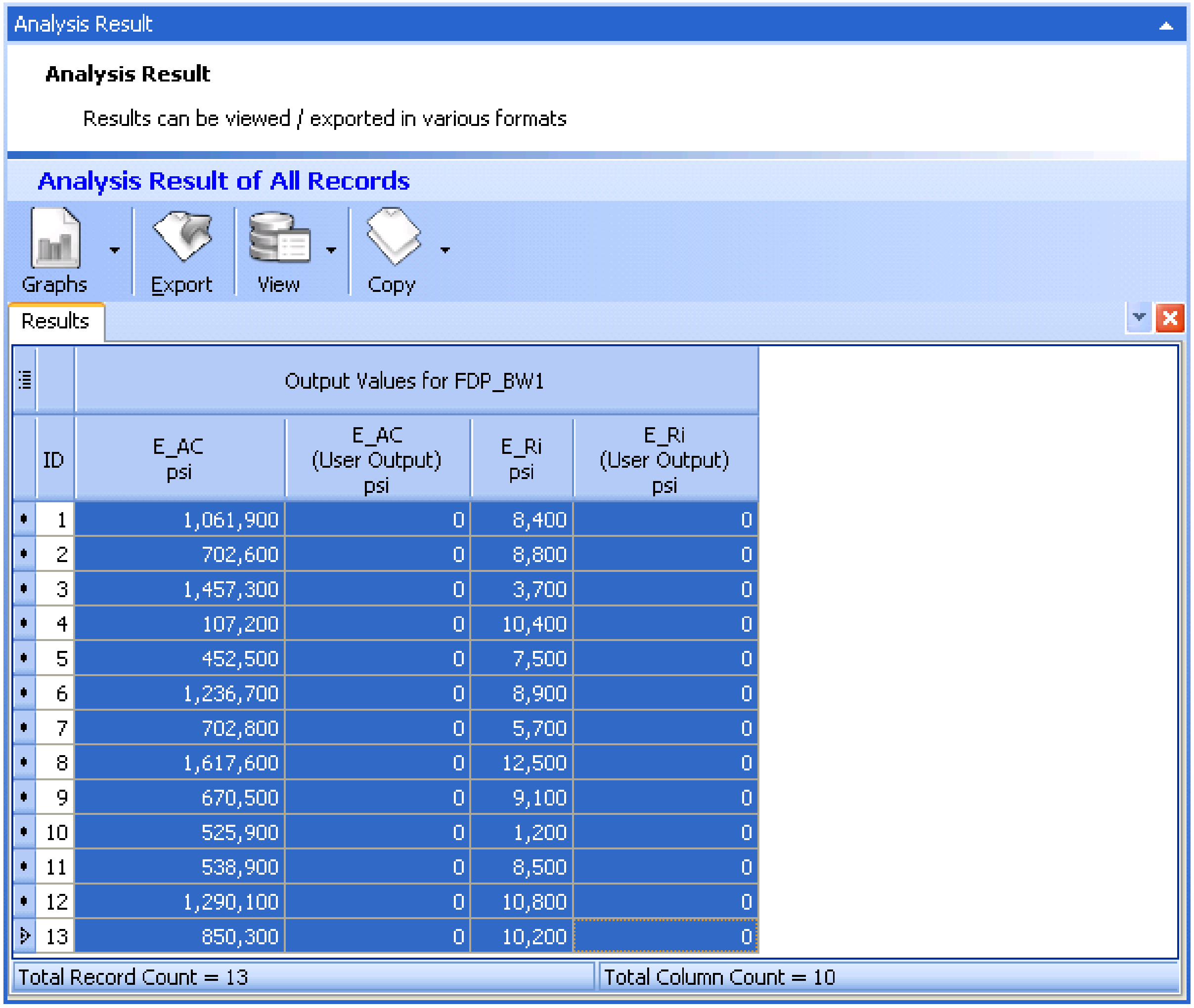


Figure 3-9. Appearance of data editor before FWD analysis (no expected output is entered).



	Output Values for FDP_BW1			
ID	E_AC psi	E_AC (User Output) psi	E_Ri psi	E_Ri (User Output) psi
1	1,061,900	0	8,400	0
2	702,600	0	8,800	0
3	1,457,300	0	3,700	0
4	107,200	0	10,400	0
5	452,500	0	7,500	0
6	1,236,700	0	8,900	0
7	702,800	0	5,700	0
8	1,617,600	0	12,500	0
9	670,500	0	9,100	0
10	525,900	0	1,200	0
11	538,900	0	8,500	0
12	1,290,100	0	10,800	0
13	850,300	0	10,200	0

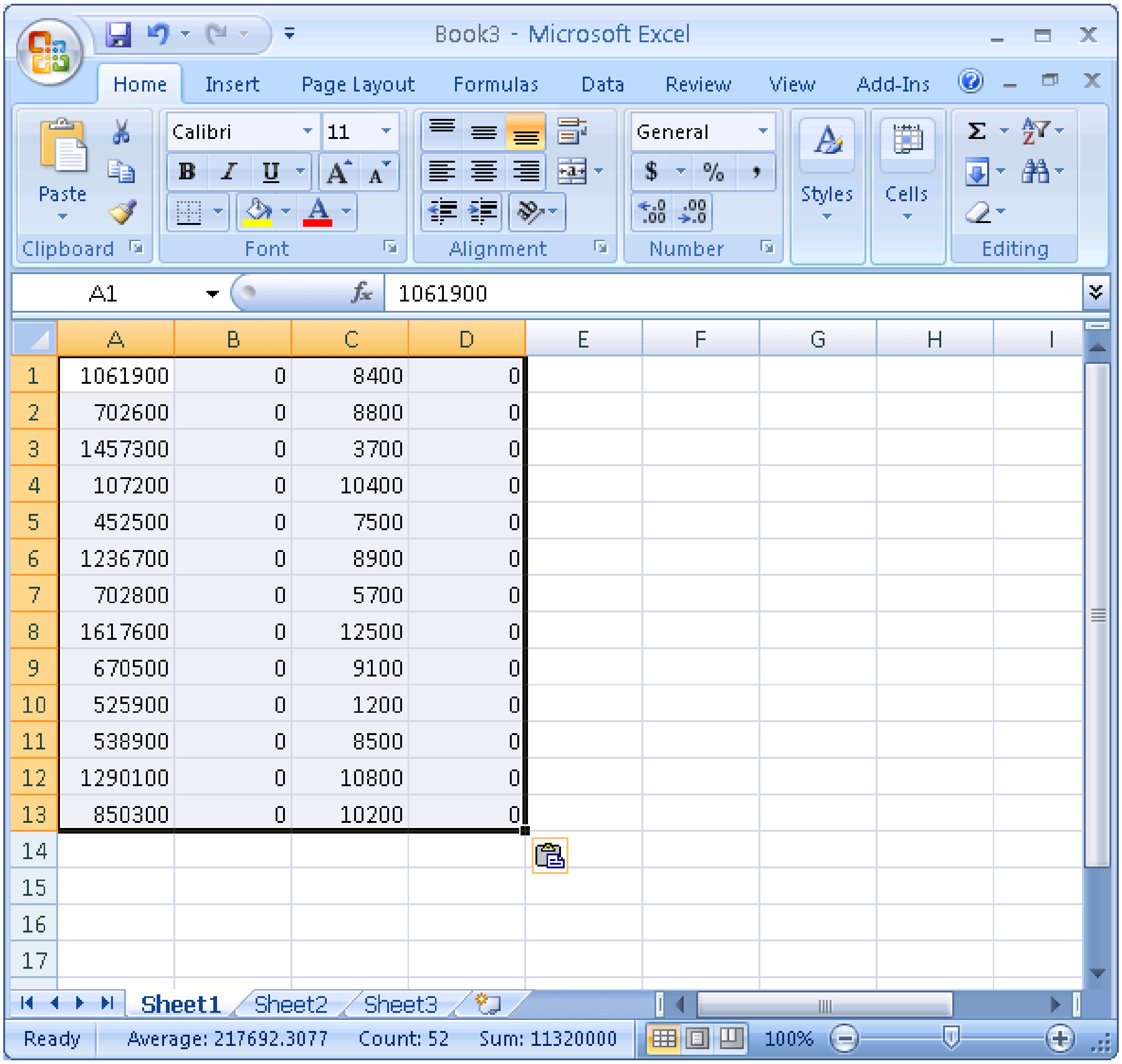
Figure 3-10. Appearance of results windows after FWD analysis.



	Output Values for FDP_BW1			
ID	E_AC psi	E_AC (User Output) psi	E_Ri psi	E_Ri (User Output) psi
1	1,061,900	0	8,400	0
2	702,600	0	8,800	0
3	1,457,300	0	3,700	0
4	107,200	0	10,400	0
5	452,500	0	7,500	0
6	1,236,700	0	8,900	0
7	702,800	0	5,700	0
8	1,617,600	0	12,500	0
9	670,500	0	9,100	0
10	525,900	0	1,200	0
11	538,900	0	8,500	0
12	1,290,100	0	10,800	0
13	850,300	0	10,200	0

Total Record Count = 13 | Total Column Count = 10

Figure 3-11. Selected results data to export into MS Excel.



	A	B	C	D
1	1061900	0	8400	0
2	702600	0	8800	0
3	1457300	0	3700	0
4	107200	0	10400	0
5	452500	0	7500	0
6	1236700	0	8900	0
7	702800	0	5700	0
8	1617600	0	12500	0
9	670500	0	9100	0
10	525900	0	1200	0
11	538900	0	8500	0
12	1290100	0	10800	0
13	850300	0	10200	0

Figure 3-12. Copied results in the empty MS Excel sheet.

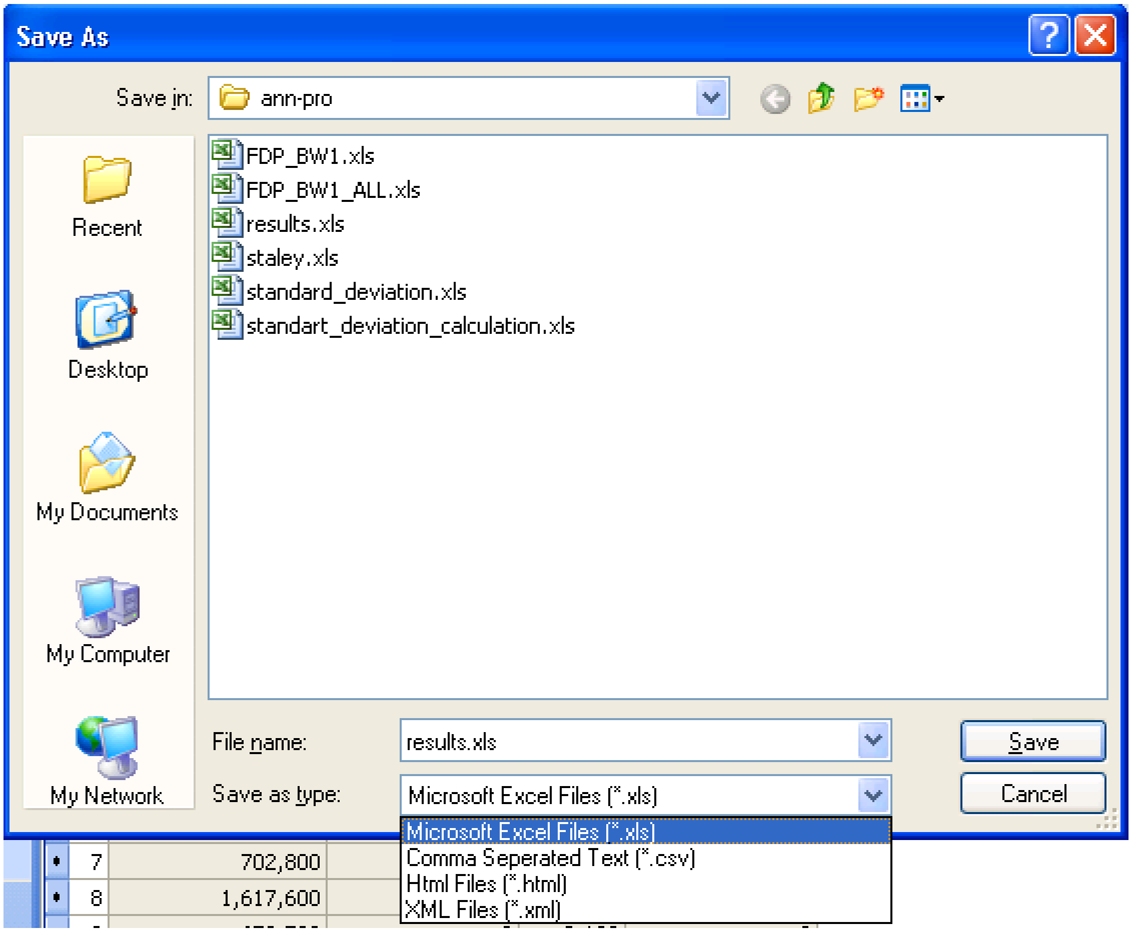
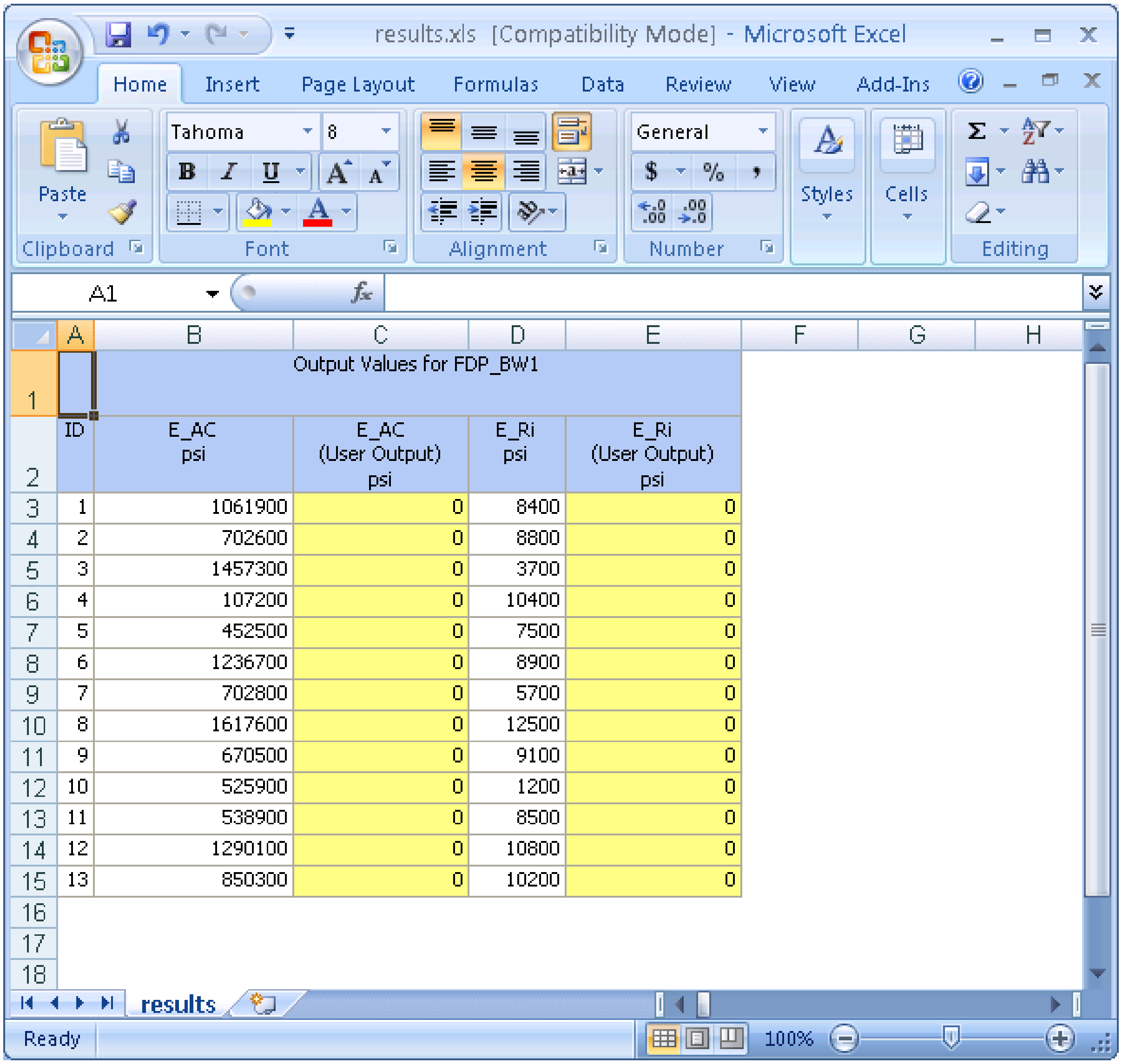


Figure 3-13. Copied results in the empty MS Excel sheet with save option.



ID	E_AC psi	E_AC (User Output) psi	E_Ri psi	E_Ri (User Output) psi
1	1061900	0	8400	0
2	702600	0	8800	0
3	1457300	0	3700	0
4	107200	0	10400	0
5	452500	0	7500	0
6	1236700	0	8900	0
7	702800	0	5700	0
8	1617600	0	12500	0
9	670500	0	9100	0
10	525900	0	1200	0
11	538900	0	8500	0
12	1290100	0	10800	0
13	850300	0	10200	0

Figure 3-14. Exported results in MS Excel.

DEFINING CUSTOM COLUMNS

Backcalculation analysis is usually based on the deflections obtained through FWD testing. Importing deflection data is therefore a major first step in backcalculation analysis. However, one may need to input extra information such as temperature, pavement layer thickness, etc. to have a complete database. For such instances, ANN-Pro provides opportunity to add custom columns in the data editor. To illustrate the details of this feature, surface temperature information will be added to each station for the whole test section. Figure 3-9 shows the data editor with the datasets already imported by some means such as by direct copy and paste or by defining data area, etc. The steps for defining custom columns are as follows:

1. In the data editor toolbar, click on Custom Columns button. Custom Columns wizard is shown on the screen. Click on Add button on this form (Figure 3-15). A new column name, a data type and the display format are automatically created for the user.

2. To change the column name to Temperature, click on new column cell and type the name of the variable. The unit information can also be entered on the same cell. The data type should be compatible with the type of temperature data. Since temperature can be a floating number, Double type can be selected (Figure 3-16). Other types are limited with integer and string for the end users in ANN-Pro. To use ANN-Pro scripts (see running scripts) along with the custom columns, the custom column type should either be integer or double. Click OK to create the custom column. Default display format can be left unchanged.
3. The temperature column can be viewed on the data editor as in Figure 3-17.
4. The information to be entered in each cell (row) can be assigned by selecting each of them separately. However, if the information to be entered is the same for all rows, then, “Set Selection Value” button may be used efficiently. To do this, first the column to be modified needs to be selected. Then, click Set Selection Value button in the Data Editor Toolbar (Figure 3-18). Click OK to set the value and data editor is refreshed (Figure 3-19).
5. In addition to above features, the column can be modified partially. For example, if the first five cells of the temperature column need to be modified, they need to be selected first. Set Selection Value button again needs to be used for this purpose. Figure 3-20 shows the data editor with first five cell temperature column changed to 100 degrees Fahrenheit.

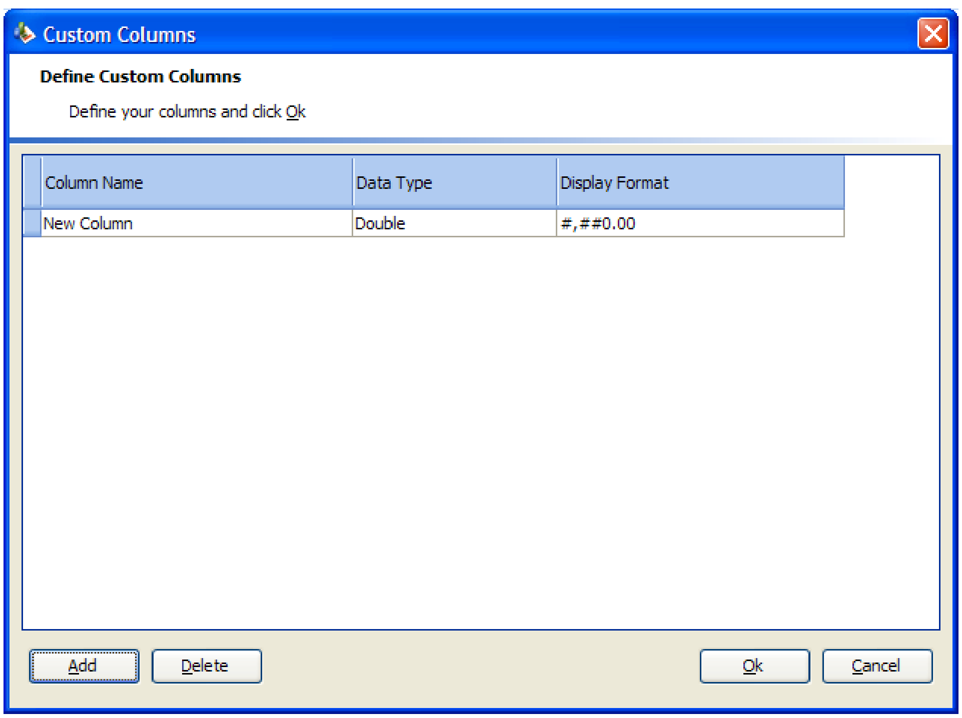


Figure 3-15. Custom column wizard.

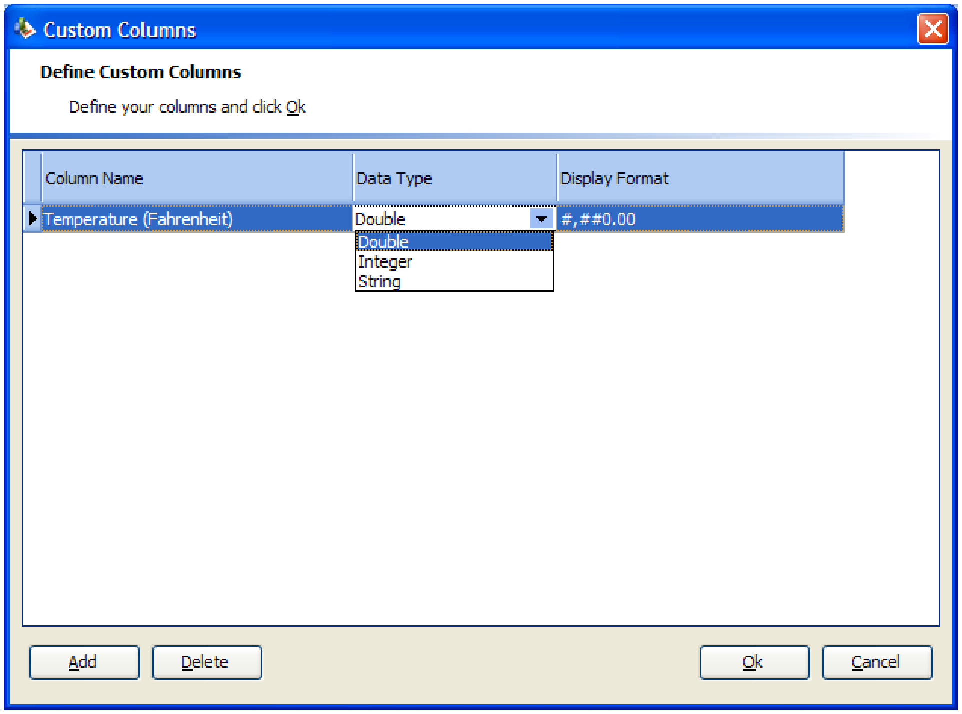


Figure 3-16. Defining temperature column using custom columns.

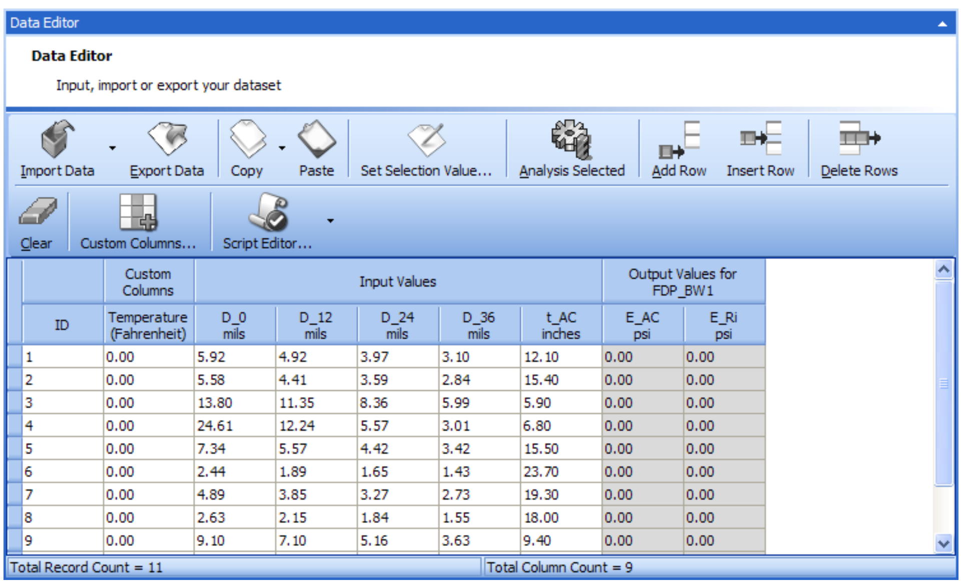


Figure 3-17. Appearance of temperature custom column in the data editor.

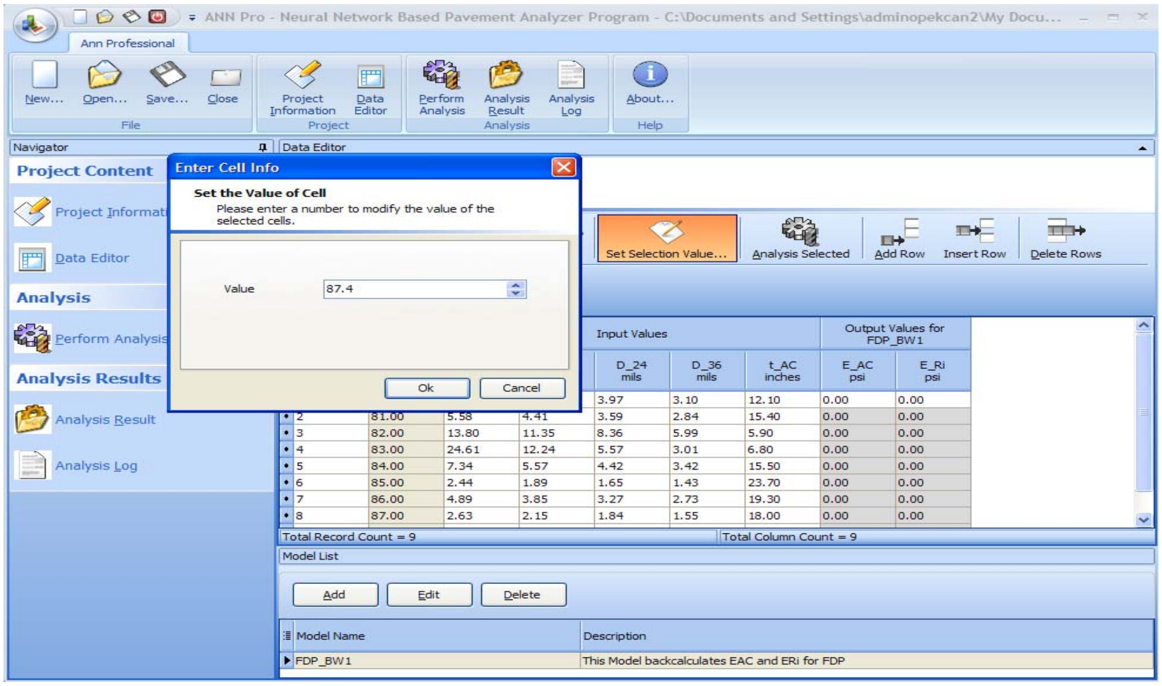


Figure 3-18. Setting the value of temperature column.

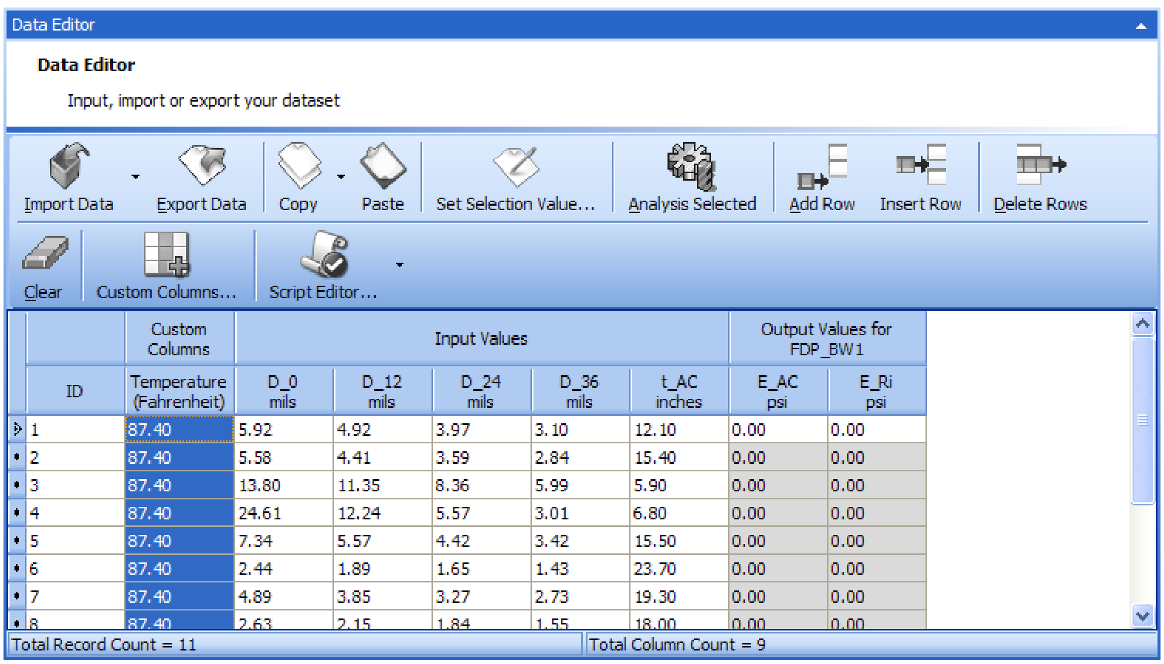


Figure 3-19. Specifying temperature values.

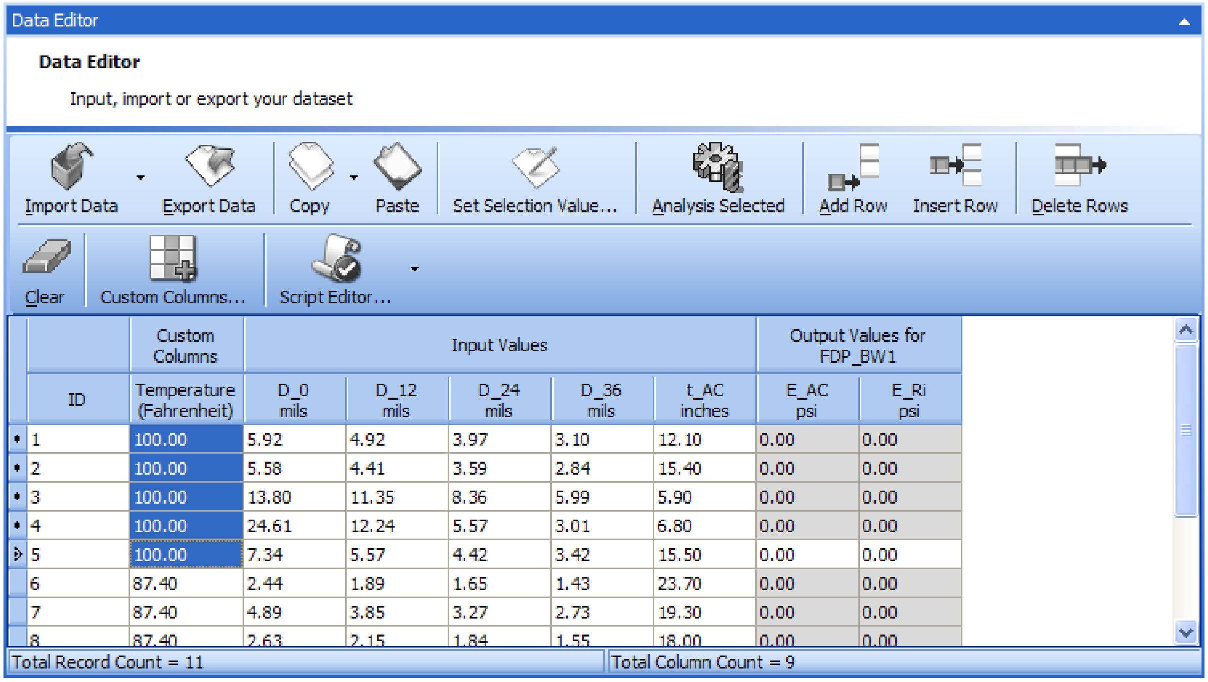


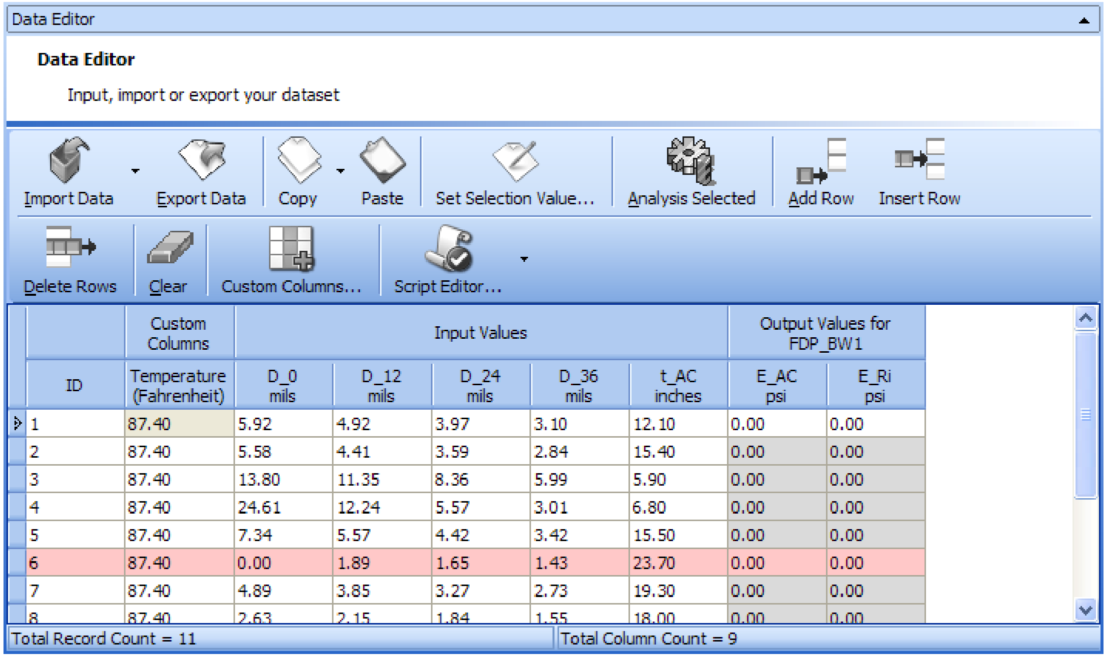
Figure 3-20. Entering temperature values.

INPUT AND OUTPUT DATA VERIFICATION

ANN-Pro Data Editor internally checks the compatibility of the data with the requirements of the ANN structural model used in the analysis. It warns the user if there is any error in the data using color schemes. It also provides a detailed error definition including the location of error, type of error, etc., in the analysis log.

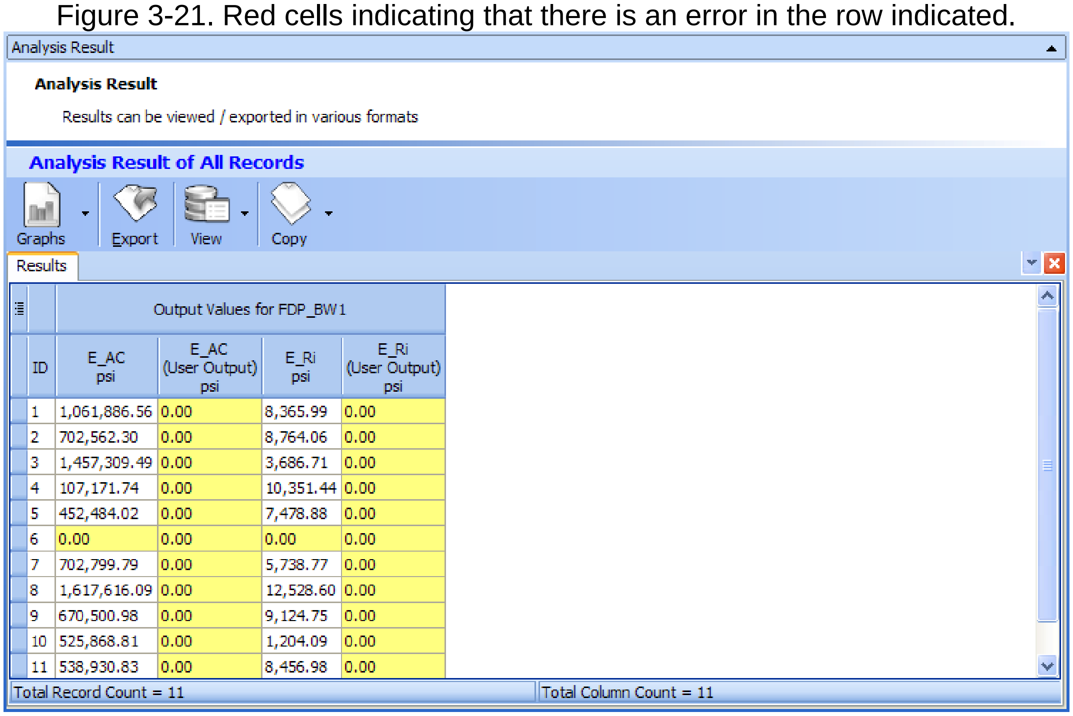
Zero and Negative Column Detection

In the above sample problem, the value of D_0 in the sixth row is intentionally changed to 0 so that ANN-Pro can determine the type and location of error (Figure 3-21). The software internally checks the data editor row-wise. If any of the cells in a row (except the ones belonging to custom columns) is zero, then, it assigns the entire row a red color. It does not process the red row in the analysis and the results are reported as zero (Figure 3-22).



	Custom Columns	Input Values					Output Values for FDP_BW1	
ID	Temperature (Fahrenheit)	D_0 mils	D_12 mils	D_24 mils	D_36 mils	t_AC inches	E_AC psi	E_Ri psi
1	87.40	5.92	4.92	3.97	3.10	12.10	0.00	0.00
2	87.40	5.58	4.41	3.59	2.84	15.40	0.00	0.00
3	87.40	13.80	11.35	8.36	5.99	5.90	0.00	0.00
4	87.40	24.61	12.24	5.57	3.01	6.80	0.00	0.00
5	87.40	7.34	5.57	4.42	3.42	15.50	0.00	0.00
6	87.40	0.00	1.89	1.65	1.43	23.70	0.00	0.00
7	87.40	4.89	3.85	3.27	2.73	19.30	0.00	0.00
8	87.40	2.63	2.15	1.84	1.55	18.00	0.00	0.00

Figure 3-21. Red cells indicating that there is an error in the row indicated.



	Output Values for FDP_BW1			
ID	E_AC psi	E_AC (User Output) psi	E_Ri psi	E_Ri (User Output) psi
1	1,061,886.56	0.00	8,365.99	0.00
2	702,562.30	0.00	8,764.06	0.00
3	1,457,309.49	0.00	3,686.71	0.00
4	107,171.74	0.00	10,351.44	0.00
5	452,484.02	0.00	7,478.88	0.00
6	0.00	0.00	0.00	0.00
7	702,799.79	0.00	5,738.77	0.00
8	1,617,616.09	0.00	12,528.60	0.00
9	670,500.98	0.00	9,124.75	0.00
10	525,868.81	0.00	1,204.09	0.00
11	538,930.83	0.00	8,456.98	0.00

Figure 3-22. Analysis log screen (yellow cells indicate the results are out of training range).

Deflection Checks

ANN-Pro inspects the consistency of the FWD deflection data. It first ensures that there is no zero deflection in the inputs. Secondly, it controls that the deflections should be smaller as they go away from the center of loading. If any of these checks fails, then the corresponding row is highlighted as red and reported in the analysis log. In the above example, D_0 should be greater than the values of other deflections D_12, D_24, etc. Since the red row is not analyzed, the error is reported in the analysis log (Figure 3-23). Finally, the deflections with values out of the training data range are indicated as yellow although they are still processed in the analyses.

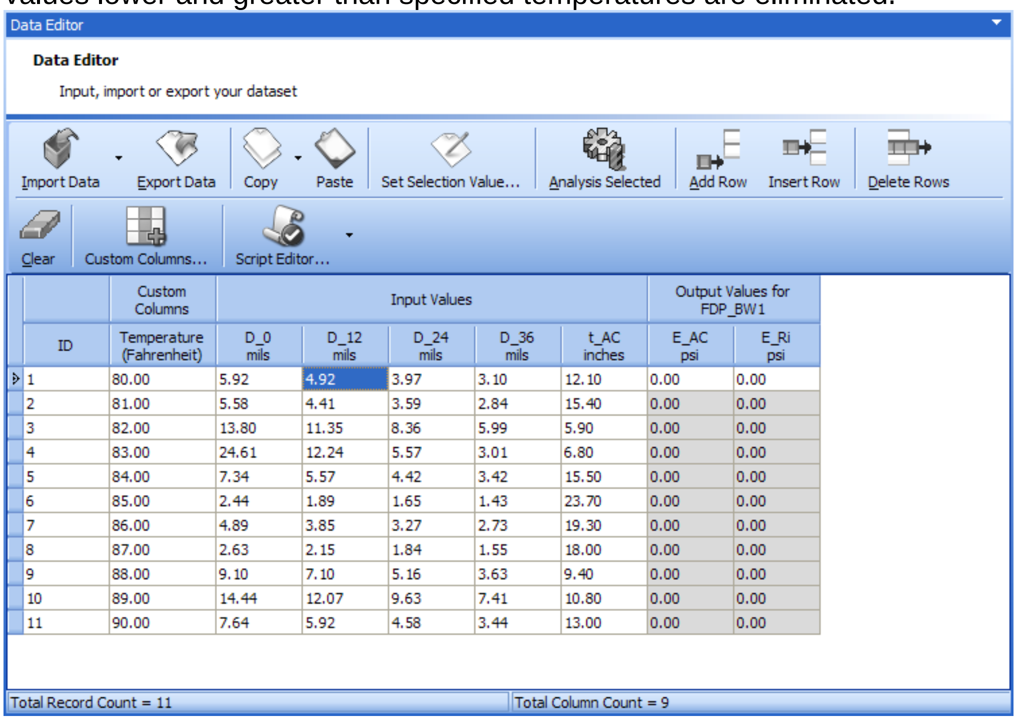
Date	Time	Type	Description
4/15/2008	2:11:26 AM	Information	Starting analysis
4/15/2008	2:11:26 AM	Information	Clearing analysis folder...
4/15/2008	2:11:26 AM		Clearing analysis folder done
4/15/2008	2:11:26 AM	Information	Checking project...
4/15/2008	2:11:26 AM	Information	Checking project done
4/15/2008	2:11:26 AM	Information	Checking for logical errors
4/15/2008	2:11:26 AM	**Error**	**Input value is zero on row 6 column D_0**
4/15/2008	2:11:26 AM	**Error**	**D_12 is greater than D_0 on row 6**
4/15/2008	2:11:26 AM	Information	Starting analysis procedure for FDP_BW1
4/15/2008	2:11:26 AM	Information	Preparing input data for FDP_BW1...
4/15/2008	2:11:26 AM	Information	Preparing input data for FDP_BW1 done
4/15/2008	2:11:26 AM	Information	Creating train set file for FDP_BW1...
4/15/2008	2:11:26 AM	Information	Creating train set file for FDP_BW1 done
4/15/2008	2:11:26 AM	Information	Running analysis for FDP_BW1...
4/15/2008	2:11:26 AM	Back Ann Log	C:\Documents and Settings\All Users\Application Data\AnnPro\Analysis> BackAnn.exe 0< Train.set

Figure 3-23. Analysis log in text format.

RUNNING ANN-PRO SCRIPTS

ANN-Pro users are commonly interested in the deflection data obtained from FWD test machines. Since these machines usually produce during testing other useful information such as surface temperature, coordinates of testing locations, etc., there may be a need to change, eliminate, or modify the data before running an analysis. For this purpose, ANN-Pro provides some scripts that allow users to work with the FWD data to perform data corrections, verifications, or modifications. ANN-Pro scripts are designed to make such data processing easier for the user. The main advantage of scripting is that users can execute their own scripts. In this section, a sample script is described to eliminate the rows with temperature value being less than 84 degree Fahrenheit and greater than 88 degree Fahrenheit. Figure 3-24 shows the data editor before the script is initiated. To run the given script, the following steps are necessary:

1. Click on the script editor and select Eliminate Rows (between) script (Figure 3-25).
2. Enter the name of the column (i.e., Temperature in degrees Fahrenheit) based on which termination criterion is defined (Figure 3-26).
3. The lower bound screen appears. The lower limit temperature of 84 degrees Fahrenheit is entered here (Figure 3-27).
4. The next screen is the upper bound one. The upper limit temperature of 88 degrees Fahrenheit is entered here (Figure 3-28). Accordingly, the rows with temperature values lower and greater than specified temperatures are eliminated.



	Custom Columns	Input Values					Output Values for FDP_BW1	
ID	Temperature (Fahrenheit)	D_0 mils	D_12 mils	D_24 mils	D_36 mils	t_AC inches	E_AC psi	E_Ri psi
1	80.00	5.92	4.92	3.97	3.10	12.10	0.00	0.00
2	81.00	5.58	4.41	3.59	2.84	15.40	0.00	0.00
3	82.00	13.80	11.35	8.36	5.99	5.90	0.00	0.00
4	83.00	24.61	12.24	5.57	3.01	6.80	0.00	0.00
5	84.00	7.34	5.57	4.42	3.42	15.50	0.00	0.00
6	85.00	2.44	1.89	1.65	1.43	23.70	0.00	0.00
7	86.00	4.89	3.85	3.27	2.73	19.30	0.00	0.00
8	87.00	2.63	2.15	1.84	1.55	18.00	0.00	0.00
9	88.00	9.10	7.10	5.16	3.63	9.40	0.00	0.00
10	89.00	14.44	12.07	9.63	7.41	10.80	0.00	0.00
11	90.00	7.64	5.92	4.58	3.44	13.00	0.00	0.00

Figure 3-24. The appearance of screen before the script is initiated.

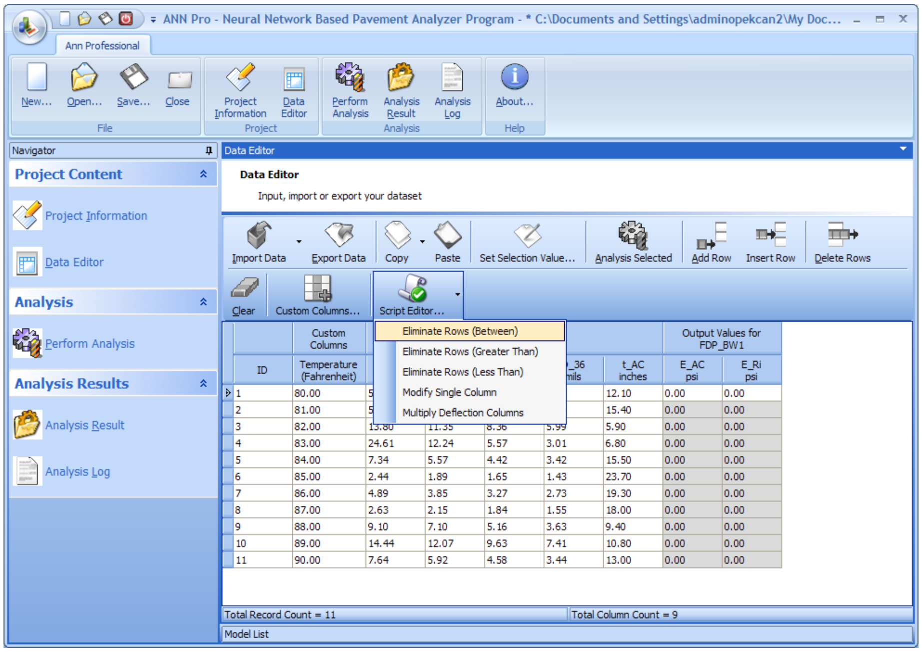


Figure 3-25. Selecting scripts on the data editor.

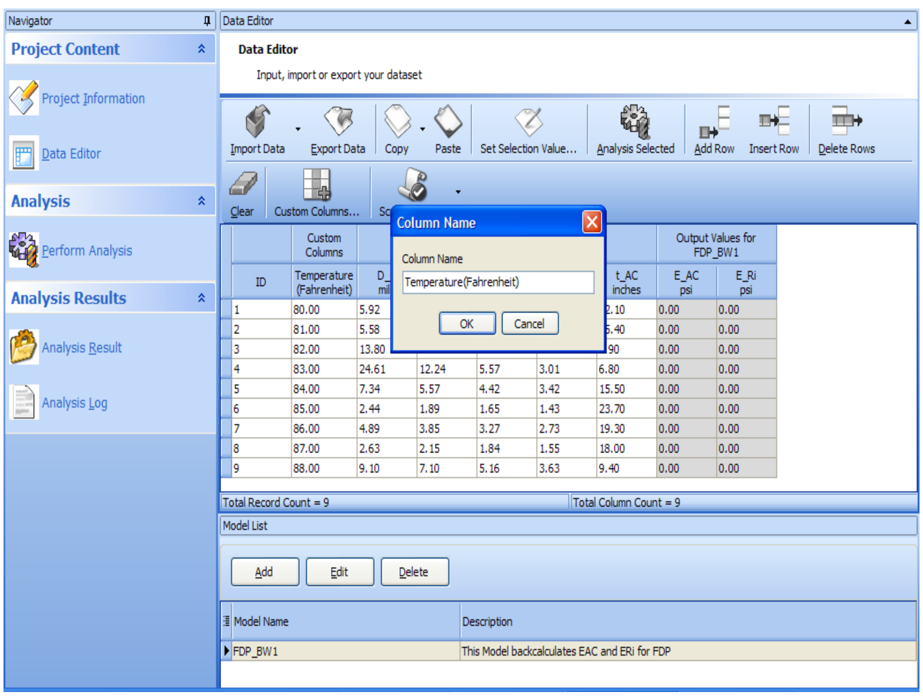


Figure 3-26. Specifying temperature column in the data editor.

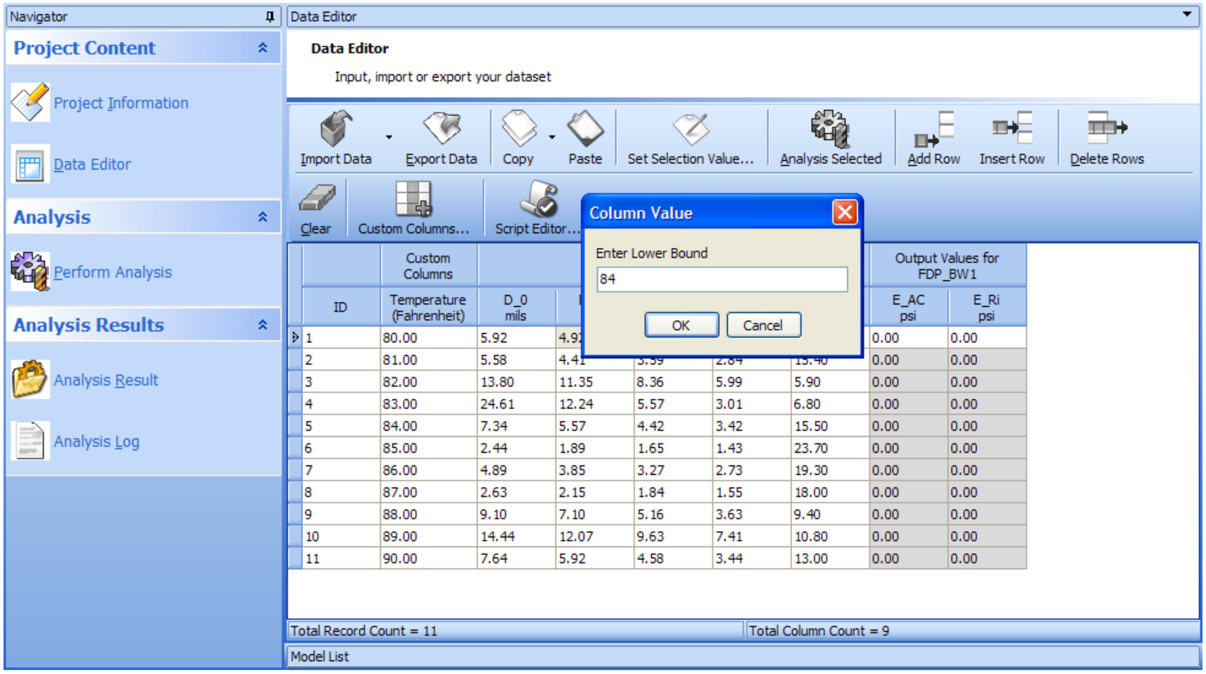


Figure 3-27. Specifying lower bound temperature in the data editor.

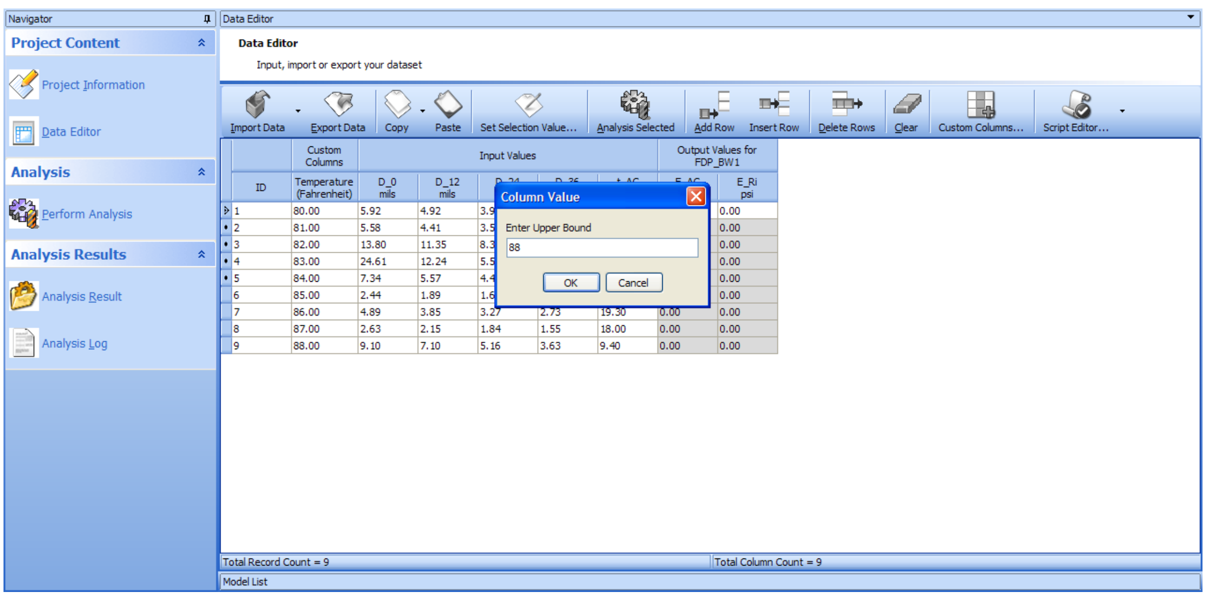


Figure 3-28. Specifying upper bound temperature in the data editor.

Introduction to ANN-Pro Scripting

ANN-Pro users can write their own scripts and execute them on the data editor. The scripting language in ANN-Pro is Pascal. Variable definitions, loops and controls can easily be written using Pascal. The idea of scripting is very similar to macros defined MS Excel. Therefore, it is expected that users familiar with writing macros in MS Excel will have no difficulty in following Pascal scripts.

A simple ANN-Pro script given in Table 3-1 illustrates the general concepts and the use of for loop and if controls. The code starts with the definition of variables using “var” keyword. Each variable requires the use of semicolon. In addition, the same type of variables can be defined on the same line by just separating those using commas. Since coding in Pascal is done in blocks, everything is written between “begin – end”. When only one row needs to be written, “begin – end” is not needed. The first “if” control needs to have block definition since it includes more than one row when it is executed. This concept is also valid for all the other control loops such as “while – end”, “repeat – end”.

In this example, the odd and even numbers are added separately and assigned to variables SumOfOdd and SumOfEven. Furthermore, the numbers are checked if their values are greater than 5 or not. The results are printed on the screen. Since the main purpose of this part is not to introduce Pascal, readers are referred to text books written for Pascal language.

Table 3-1. Sample Pascal code to illustrate the use of basic programming concepts

```
var
    I:integer;
    SumOfOdd, SumOfEven:integer;
begin
    SumOfEven := 0;
    SumOfOdd := 0;
    for I:=0 to 10 do
    begin
        if I mod 2 = 0 then
        begin
            SumOfEven := SumOfEven + I;
            ShowMessage(‘Even Number’);
        end
        else
        begin
            SumOfOdd := SumOfOdd + I;
            ShowMessage(‘Odd Number’);
        end;
        if I > 5 then
            ShowMessage(‘I > 5’)
        else
            ShowMessage(‘I <= 5’);
    end;
end;
```

ANN-Pro uses scripting only for managing the Data Editor. To use functions written using ANN-Pro scripts, first “frmMain” namespace needs to be utilized. Table 3-2 provides a sample script for deletion of all the records in model BW-1 with “D_0” value less than 10.

Table 3-2. Sample Pascal code to illustrate the use of basic programming concepts

```
 for I:=frmMain.DataEditorRecordCount - 1 downto 0 do
 begin
   if frmMain.Cell['D_0', I] < 10 then
     frmMain.DeleteRow(I);
 end;
frmMain.RefreshDataEditor;
```

ANN-Pro supports the following functions that can operate in the “frmMain”.

1. *Cell [ColumnName, RowIndex]*

It returns the value of cell whose Column Name and Row Index are specified. It has Read and Write access. For example, the second row of D_0 column can be multiplied with 2 using the following script.

frmMain.Cell[‘D_0’, 1] := frmMain.Cell[‘D_0’, 1] * 2;

2. *SetUnit (ColumnName, UnitName, UnitDescription, MultipleBy, DisplayFormat)*

This function uses to change the unit of any column.

ColumnName : The name of the column to be changed
UnitName : The name of new column unit
UnitDescription : Description of new unit
MultipleBy : New unit coefficient (generally taken as 1)
DisplayFormat : Specifies the display format

3. *GetUnitName(ColumnName)*

It returns the name of Column in string format.

ColumnName : string;

4. *GetUnitDescription(ColumnName)*

It returns the description of column unit in string format.

ColumnName : string;

5. *GetUnitMultipleBy(ColumnName)*

It returns the coefficient of any column in float variable.

ColumnName :string;

6. *GetUnitFormat (ColumnName)*

It returns the format of a unit in string.

ColumnName : string;

7. *SetUnitName(ColumnName, UnitName)*

Change the unit of the column.

ColumnName : string;
UnitName : string;

8. *SetUnitDescription(ColumnName, UnitDescription)*
It changes the description of any unit.
ColumnName : string;
UnitDescription: string;

9. *SetUnitMultipleBy (ColumnName, MultipleBy)*
It changes the coefficient of any column.
ColumnName : string;
MultipleBy : float;

10. *SetUnitFormat (ColumnName, UnitFormat)*
It changes the format of unit
ColumnName : string;
UnitFormat : string;

11. *RefreshDataEditor*
It refreshes the data editor to show the latest updates.

12. *DataEditorRecordCount*
It returns the count of record in the data editor in integer format.

13. *DeleteRow(Index:integer)*
It deletes the row given with the specified row number.
Index : integer;

14. *GetInputColumnName / GetOutputColumnName / GetCustomColumnName*
It returns the name of the column with the given index.
Index : integer;

15. *GetCustomColumnCount / GetInputColumnCount / GetOutputColumnCount*
It provides the number of Input, Output and Custom columns.
The following scripts given in Tables 3-3 through 3-6 are the ones implemented in ANN-Pro. These will be enhanced in the future versions of the program. The users are strongly encouraged to examine them to extend the capabilities of the software for future needs.

Table 3-3. Pascal Code for Eliminating Rows (Between)

```
var
  I, K:integer;
  LowerBound:double;
  UpperBound:double;
  LowerBoundStr:string;
  UpperBoundStr:string;
  SourceColumnName:string;
begin
  SourceColumnName := frmMain.InputBox('Column Name', 'Column Name', 'load');
  if SourceColumnName = '' then Exit;

  LowerBoundStr := frmMain.InputBox('Column Value', 'Enter Lower Bound', '9000');
  if LowerBoundStr = '' then Exit;

  UpperBoundStr := frmMain.InputBox('Column Value', 'Enter Upper Bound', '9000');
  if UpperBoundStr = '' then Exit;

  try
    LowerBound := StrToFloat(LowerBoundStr);
    UpperBound := StrToFloat(UpperBoundStr);
  except
    ShowMessage('Upper and Lower bound values should be floating (real) numbers');
    Exit;
  end;

  if LowerBound >= UpperBound then
  begin
    ShowMessage('Lower Bound should be less than the upper Bound!');
    Exit;
  end;

  for I:=frmMain.DataEditorRecordCount - 1 downto 0 do
  begin
    if frmMain.Cell[SourceColumnName, I] < UpperBound then
      frmMain.DeleteRow(I);
    if frmMain.Cell[SourceColumnName, I] > LowerBound then
      frmMain.DeleteRow(I);
  end;
  frmMain.RefreshDataEditor;
end;
```

Table 3-4. Pascal Code for Eliminating Rows (Less Than)

```
var
  I, K:integer;
  SourceValue:double;
  SourceValueStr:string;
  SourceColumnName:string;
begin
  SourceColumnName := frmMain.InputBox('Column Name', 'Column Name', 'load');
  if SourceColumnName = '' then Exit;

  SourceValueStr := frmMain.InputBox('Column Value', 'Please type column value', '9000');
  if SourceValueStr = '' then Exit;

  try
    SourceValue := StrToFloat(SourceValueStr);
  except
    ShowMessage('Column Value should be float');
    Exit;
  end;

  for I:=frmMain.DataEditorRecordCount - 1 downto 0 do
  begin
    if frmMain.Cell[SourceColumnName, I] < SourceValue then
      frmMain.DeleteRow(I);
  end;
  frmMain.RefreshDataEditor;
end;
```

Table 3-5. Pascal Code for Multiplying Deflection Columns

```
function LeftStr(AString:string; Count:integer):string;
var
   I:integer;
begin
     Result := '';
     for I:=1 to Count do
          Result := Result + AString[I];
end;
var
  I, K:integer;
  OutputColumnCount:integer;
  ColName:string;
  MultipleByColumnName:string;
begin
  MultipleByColumnName := frmMain.InputBox('Column Name', 'Please type column name',
'load');
  if MultipleByColumnName = '' then Exit;

  OutputColumnCount := frmMain.GetOutputColumnCount;

  for I:=0 to frmMain.DataEditorRecordCount - 1 do
  begin
    for K:=0 to OutputColumnCount - 1 do
    begin
         ColName := frmMain.GetOutputColumnName(K);
         if LeftStr(ColName, 2) = 'D_' then
            frmMain.Cell[ColName, I] := frmMain.Cell[ColName, I] *
frmMain.Cell[MultipleByColumnName, I];
    end;
  end;
  frmMain.RefreshDataEditor;
end;
```

Table 3-6. Pascal Code for Modifying Single Columns

```
var
  I:integer;
  ColName:string;
  MultipleByStr:string;
  MultipleBy:double;
begin
  ColName := frmMain.InputBox('Column Name', 'Please type column name', 'D_0');
  if ColName = '' then Exit;

  MultipleByStr := frmMain.InputBox('Multiply By', 'Please enter a number to multiply', '1');
  try
    MultipleBy := StrToFloat(MultipleByStr);
  except
    ShowMessage('Invalida floating value');
    Exit;
  end;

  for I:=0 to frmMain.DataEditorRecordCount - 1 do
  begin
    frmMain.Cell[ColName, I] := frmMain.Cell[ColName, I] * MultipleBy;
  end;
  frmMain.RefreshDataEditor;
end;
```

APPENDIX B

Soft Computing Based Pavement and Geomaterial System Identifier
SOFTSYS
Version 0.1.0.0

User's Manual

CONTENTS

CHAPTER 1: INTRODUCTION

SOFTWARE REQUIREMENTS

SOFTSYS is an SOFTSYS has been developed to perform the following task in real time as part of conducting FWD tests:

- Determination of pavement thickness
- Estimation of pavement moduli
- Identifying pavement parameters such as poisons ratio

SOFTSYS interprets FWD test results and performs pavement structural analysis based on the Finite Element Method (FEM). FEM provides modeling of pavement structure due to applied wheel loading to compute pavement deflections. FEM internally captures the nonlinear material properties to simulate the real pavement behavior. SOFTSYS, therefore, has an inherent capability of incorporating the nonlinear properties of aggregate and soil layers underneath pavements. Unlike the linear elastic theory commonly used in pavement analysis, nonlinear unbound aggregate base and subgrade soil characterization models are used in the FEM. This accounts for the typical hardening behavior of unbound aggregate bases and softening nature of fine-grained subgrade soils under increasing stress states. The results of the nonlinear finite element approach have been proven to be consistent with the deflections obtained from NDT of pavements.

SOFTSYS program was developed for computers running on MS Windows environment. It is intended to operate both in Windows XP and Windows Vista operating systems. Adaptation to newer operating systems that may appear on the market in the future can be assured with very minor modifications.

SOFTSYS was developed in MATLAB® using sequential programming (SP) principles. The coding was done using MATLAB 2007b. Some additional components such as Fortran executable were also used in the program. However, MATLAB® program is not required to run SOFTSYS since the executable file is included with the SOFTSYS installation package.

HARDWARE REQUIREMENTS

An Intel Pentium III processor with 667 MHz clock speed is suggested as the minimum for practical purposes. Naturally, the older the system, the longer it takes to setup the software or to run analyses. Therefore, it is also suggested that users have recently manufactured processor to have agreeably faster operations with the software. In addition, a minimum of 512 KB of randomized memory (RAM) is recommended for effective use of the software. There is no specific requirement for graphics processor.

PROGRAM SETUP

SOFTSYS software is distributed as two zipped files;

- MCRInstaller.zip (Includes MATLAB Compiler Installer)

- SSS.zip (Includes SoftSys Files)

The user must unzip both files. Each file needs to be setup separately. First, MCRInstaller file should be unzipped into any existing folder. Then, “MCRInstaller.exe” file should be clicked to open and install the software.

Using the MCR Installer

1. When the MCR Installer wizard appears, click Next to begin the installation. Then, click Next to continue.
2. In the Select Installation Folder dialog box, specify where you want to install the MCR and whether you want to install the MCR for just yourself or others. Click Next to continue. (Note the Install MATLAB® Compiler™ Runtime for yourself, or for anyone who uses this computer option is not implemented for this release. The current default is Everyone.)

3. Confirm your selections by clicking Next.

4. The installation begins. The process takes some time due to the quantity of files that are installed. The MCRInstaller automatically:

Copies the necessary files to the target directory you specified;
Registers the components as needed;
Updates the system path to point to the MCR binary directory, which is <target_directory>/<version>/runtime/bin/win32.
When the installation is complete, click Close on the Installation Completed dialog box to exit.

The second .zip file (SSS.zip) needs to be installed after MCRInstaller is set up in the computer. It contains the all the files necessary to run SOFTSYS.

INSTALLING SOFTSYS FILES

1. The user needs to create a folder named “SSS”, which stands for SOFTSYS, under the main directory C (or whatever letter designates the hard drive directory in the personal computer);
2. The installation directory should be “C:\SSS”. When all the files are uninstalled, the appearance of the directory becomes as follows:

   C:\ SSS \ v1_0 \ ANN

   C:\ SSS \ v1_0 \ Code

   C:\ SSS \ v1_0 \ FWD

   C:\ SSS \ v1_0 \ Results

3. The user should not change the content of ANN, Results and Code directories. Otherwise, SOFTSYS may not run properly.

CHAPTER 2: RUNNING A SAMPLE SOFTSYS ANALYSIS

1. Assume that a sample FWD data file (IP-SYNTH_Road_Data.xls) is already available under “C:\SSS\v1_0\FWD\FDP\IP-SYNTH” directory (Figure 2-1) (A sample file, “IP-SYNTH_Road_Data.xls”, is provided in the setup file). If a different road needs to be analyzed, then a different file with the same format needs to be saved in the following directory “C:\SSS\v1_0\FWD\FDP\EXAMPLE-FILE\EXAMPLE-FILE_Road_Data.xls” This is a MS Excel file and the user needs to modify it to analyze a different FWD file. It is recommended that the user should keep the same format while modifying the numbers. The column headings clearly explain the variable names. Number represents the station number and E_{AC} and E_{RI} are the user estimates of the asphalt concrete and subgrade moduli for the full depth asphalt pavement analyzed. If the user does not have typical estimates, these columns should be entered 0 for SOFTSYS to run. The columns D_{0}, D_{12}, D_{24}, D_{36} are the FWD deflections.
2. There are two files under Code directory: “settings.ini” and “sss_loader.exe”. Settings file should not be modified for SOFTSYS to run properly. The SOFTSYS executable file “sss_loader.exe” needs to be clicked on to run SOFTSYS.

3. When the executable “sss_loader.exe” is clicked, the program asks for a number to initiate the backcalculation analyses (Figure 2-2). It is recommended that the same number should not be entered in two consecutive analyses.

4. The program automatically determines the location of files based on the date and time of analysis and prints them on the screen (Figure 2-3). The combination of time and date including years will be used as folder name where the results will be stored. Then, the analyses start for all FWD stations available in the MS Excel file. The generations, i.e., iterations, are shown on the screen (Figures 2-4 to 2-6).

5. The progress of SOFTSYS is shown on the screen when the analysis of all FWD station is finished successfully (Figure 2-7).

6. The graphical results are shown on the screen (Figures 2-8 to 2-10) and saved under the results folder.

7. The results will also be stored in the MS Excel (“IP-SYNTHRoad.csv”) file found in results directory (Figure 2-11).

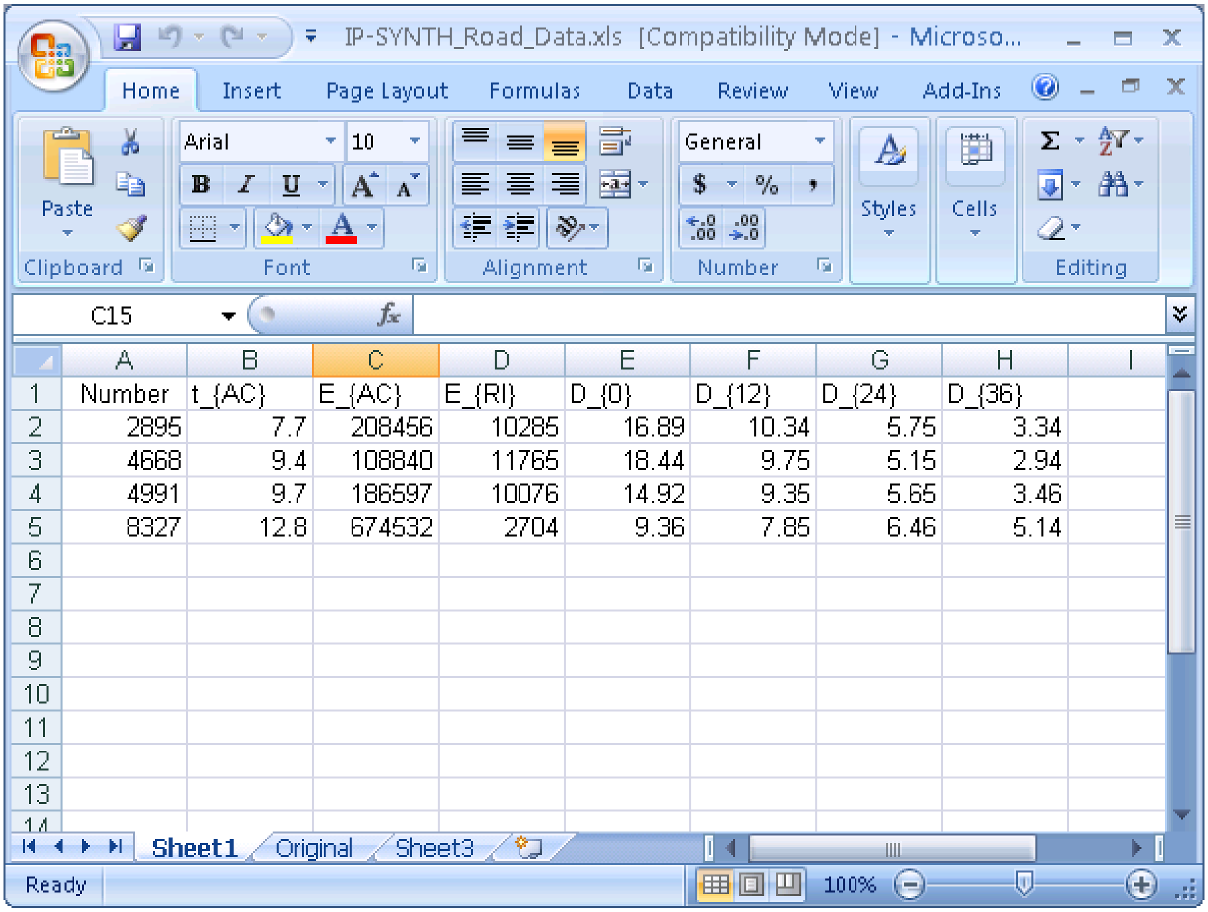


Figure 2-1. Appearance of the FWD file to be analyzed.

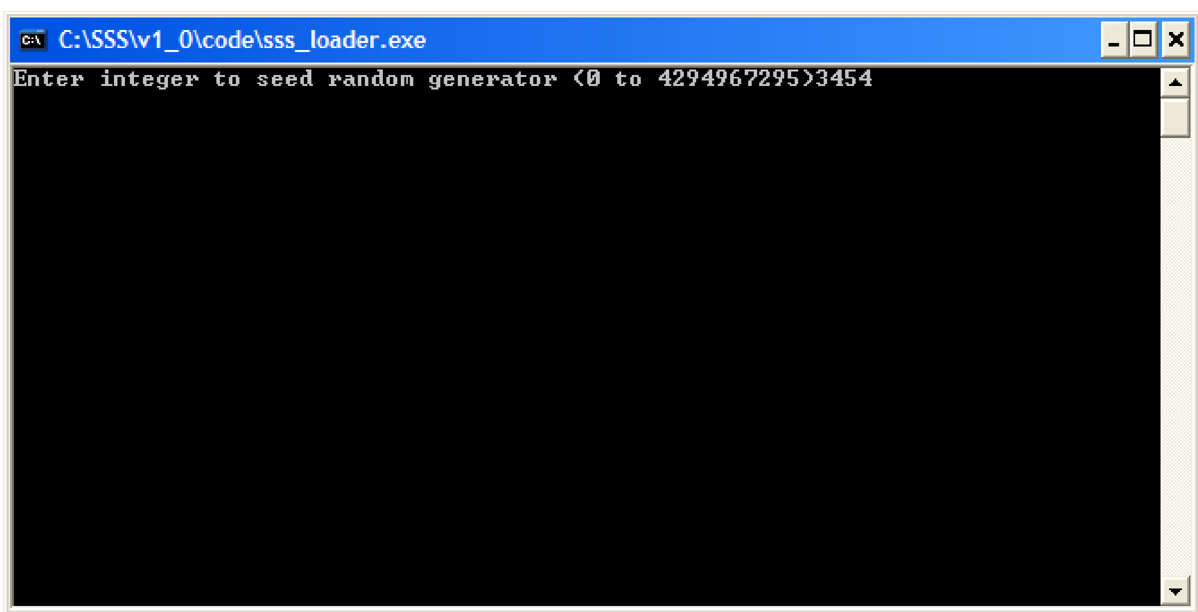


Figure 2-2. Entering a number to seed random number generator.

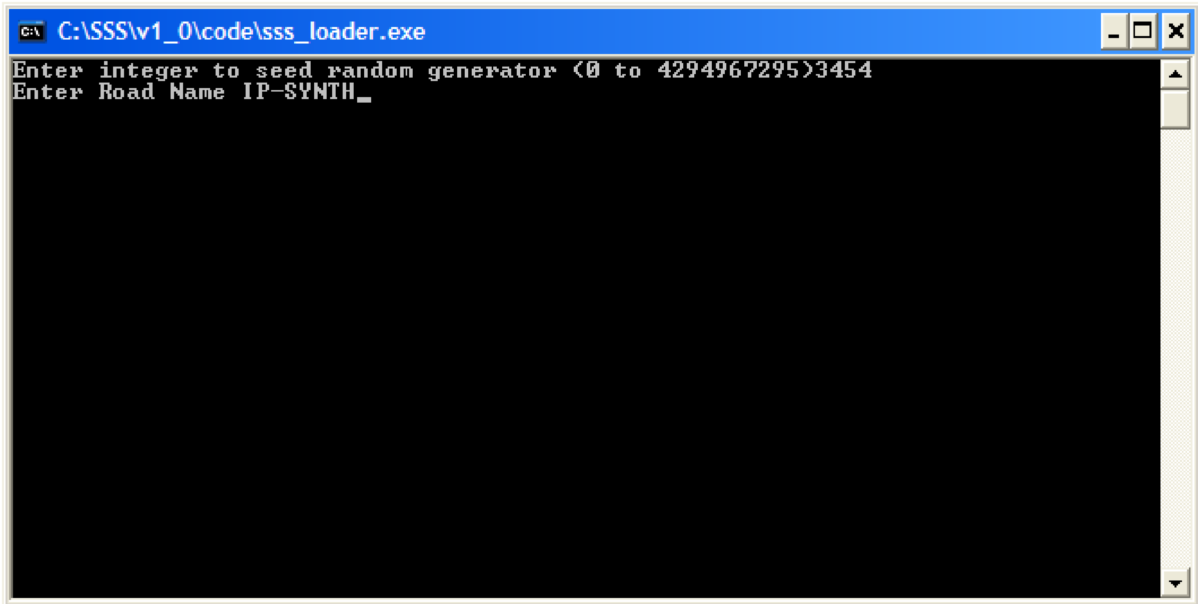


Figure 2-3. Dynamic folder name definition.

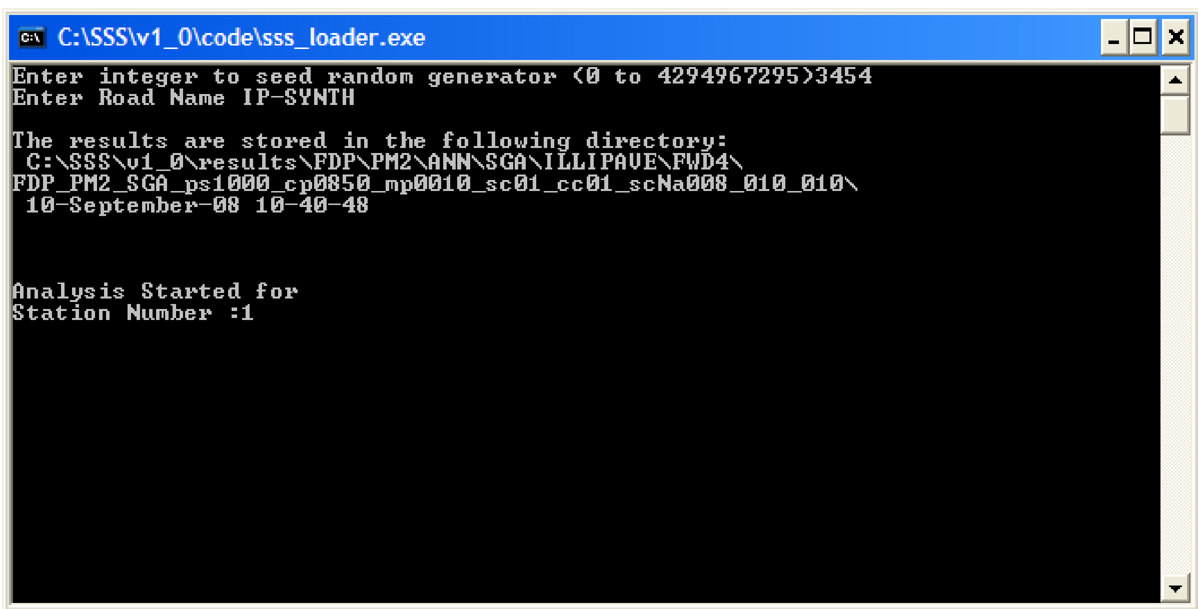


Figure 2-4. Progress of SOFTSYS through generations.

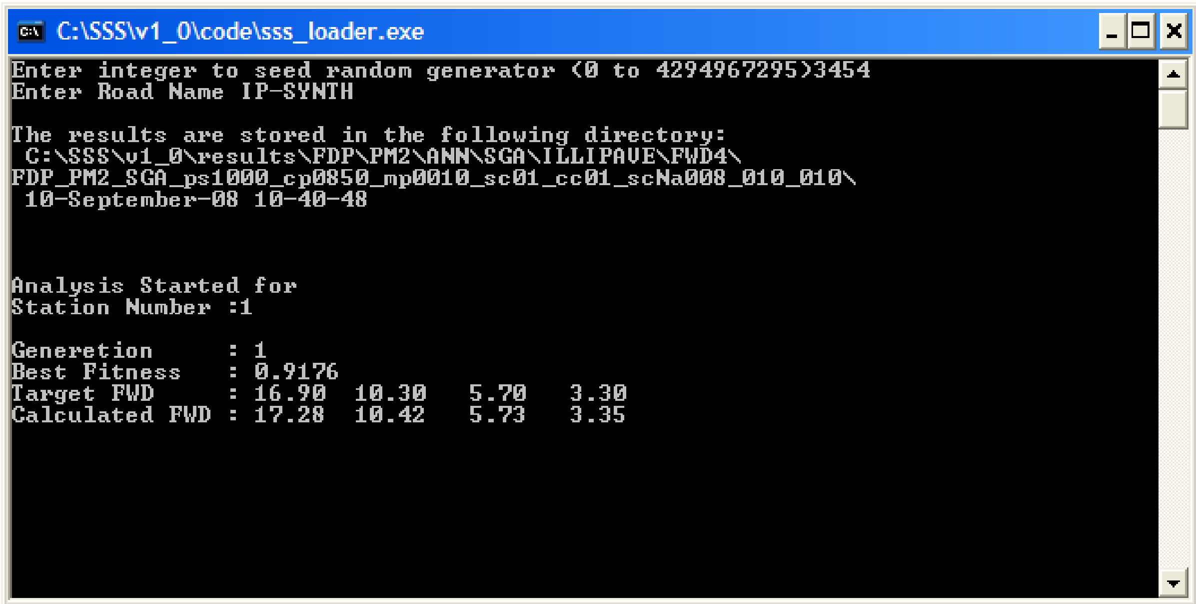


Figure 2-5. Initial progress of SOFTSYS.

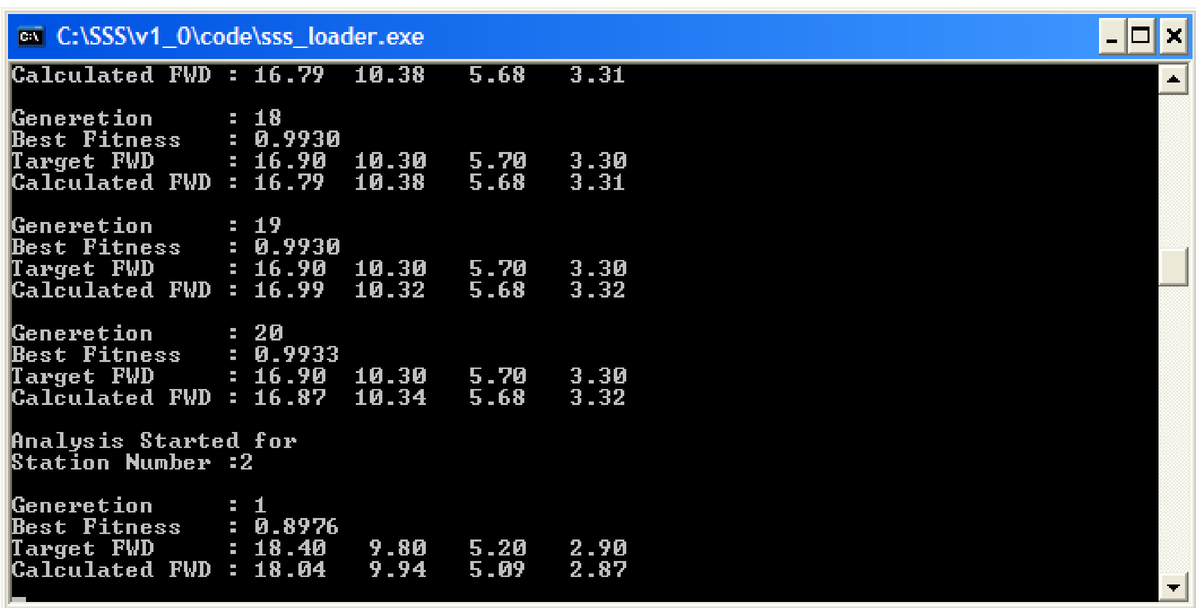


Figure 2-6. Finishing of analysis only one station in SOFTSYS.

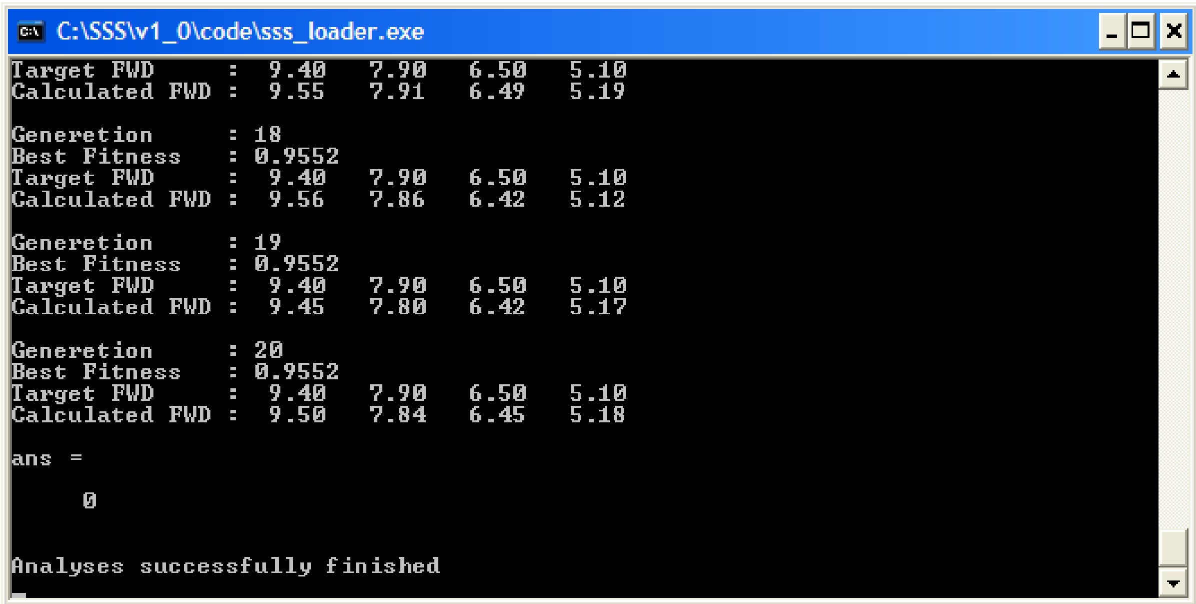


Figure 2-7. Finish of analysis in SOFTSYS.

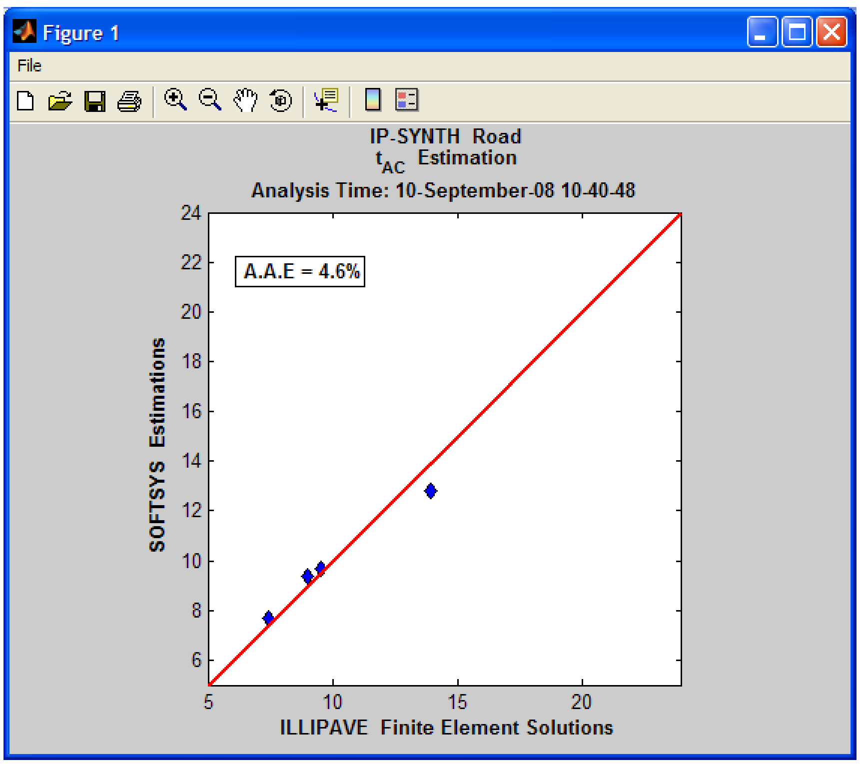


Figure 2-8. Graphical comparison of estimated results vs. calculated ones for thickness.

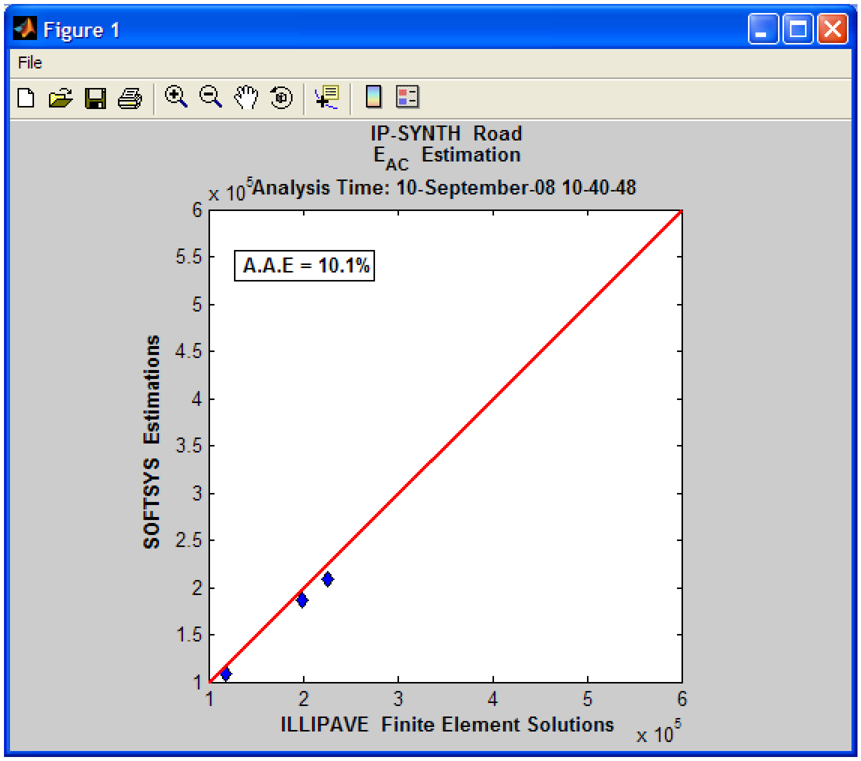


Figure 2-9. Graphical comparison of estimated results vs. calculated ones for asphalt concrete layer moduli.

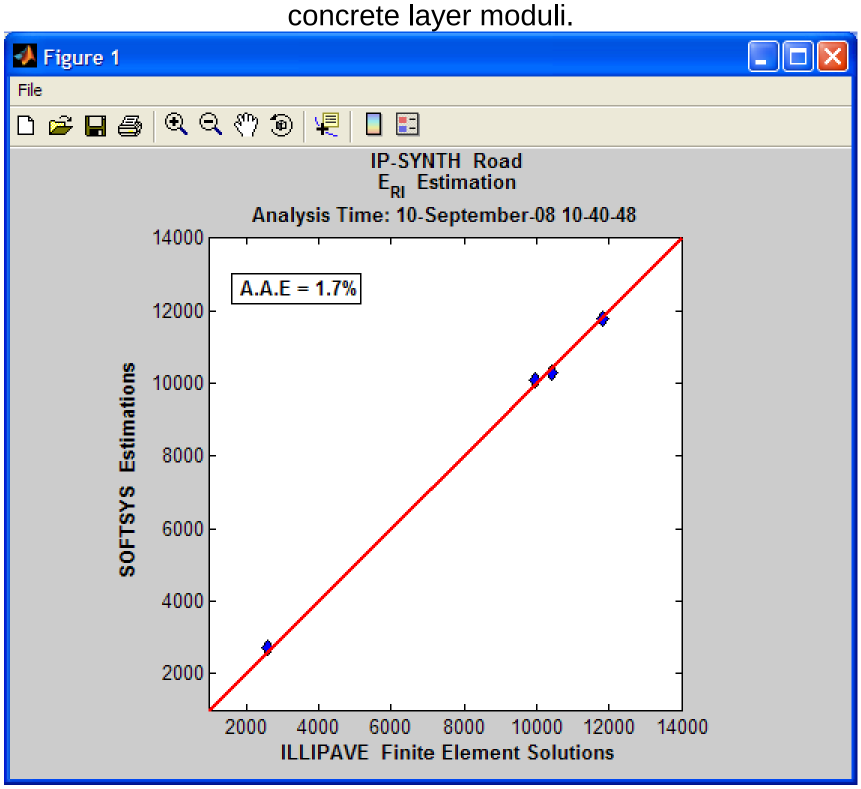
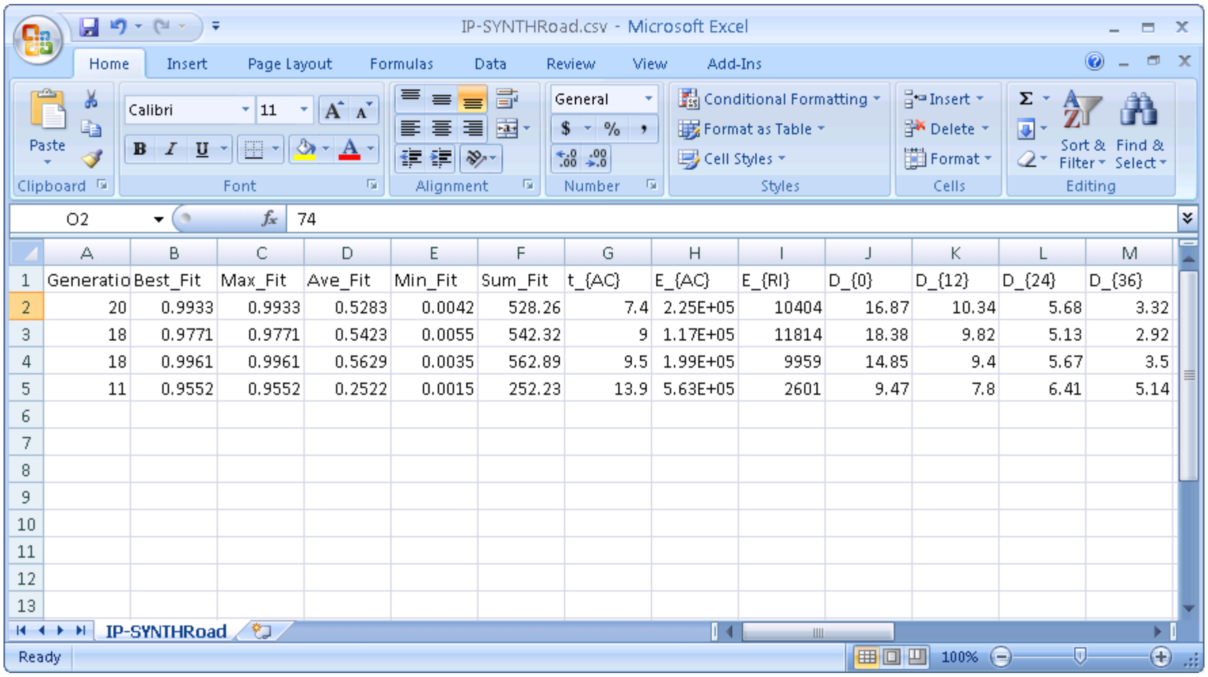


Figure 2-10. Graphical comparison of estimated results vs. calculated ones for subgrade layer moduli.



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Generatio	Best_Fit	Max_Fit	Ave_Fit	Min_Fit	Sum_Fit	t_{AC}	E_{AC}	E_{RI}	D_{0}	D_{12}	D_{24}	D_{36}
2	20	0.9933	0.9933	0.5283	0.0042	528.26	7.4	2.25E+05	10404	16.87	10.34	5.68	3.32
3	18	0.9771	0.9771	0.5423	0.0055	542.32	9	1.17E+05	11814	18.38	9.82	5.13	2.92
4	18	0.9961	0.9961	0.5629	0.0035	562.89	9.5	1.99E+05	9959	14.85	9.4	5.67	3.5
5	11	0.9552	0.9552	0.2522	0.0015	252.23	13.9	5.63E+05	2601	9.47	7.8	6.41	5.14

Figure 2-11. Appearance of results file.

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